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Variability in agricultural productivity and rural household consumption inequality

Evidence from Nigeria and Uganda

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ABSTRACT

This paper uses multiple rounds of household survey panel data to assess the distributional implications of variability in agricultural productivity in Nigeria and Uganda. It uses both a conventional decomposition and a regression-based inequality decomposition to estimate the impact of climate-induced variability in agricultural productivity. To mitigate the endogeneity associated with unobserved time-invariant and time-variant household fixed effects, we use rainfall shocks as a proxy for estimating the exogenous variability in agricultural productivity that affects consumption. Results suggest that a 10 percent increase in the variability of agricultural productivity tends to decrease household consumption by 38 and 52 percent on average for Nigeria and Uganda, respectively. Controlling for other factors, variability in agricultural productivity contributed to between 25 and 43 percent of consumption inequality between 2010 and 2015 for Nigeria; and 16 and 31 percent of consumption inequality between 2009 and 2011 for Uganda. We also show that variability in agricultural productivity increases changes in consumption inequality over time.

Keywords: climate shocks, agricultural productivity, consumption, inequality, rural, Nigeria, Uganda

1. INTRODUCTION

Economic inequality can hamper economic growth, hurt social cohesion, sometimes leading to conflict, and slow poverty reduction efforts. The benefits of productivity growth, including those in agriculture, often accrue to higher income households (Berg et al. 2012; Stiglitz 2012; Thirtle et al. 2003; Marrero & Rodriguez 2013). Growth among the wealthy does not always trickle down to the poor. Therefore, the reduction of inequality is an important development objective on its own merit (Shepherd et al. 2014). Sub-Saharan Africa (SSA), in particular, has greater inequality in living standards than that seen in any other region except Latin America and the Caribbean (Sahn & Stifel 2003 2000; Okojie & Shimeles 2006). Inequality in the SSA region has remained high over the past two decades, with regional Gini coefficient indices of 0.52 in 1993 and 0.56 in 2008 (Beegle et al. 2016). Rising inequality may reflect a lack of economic opportunity and may itself limit the growth potential of economies by not allowing all economic agents to fully exploit new opportunities (Marrero et al. 2016; Jaumotte et al. 2013).

For many rural households, improving agricultural productivity growth is considered the key pathway out of poverty (Binswanger & Townsend 2000; Christiaensen et al. 2011; Collier and Dercon 2014; Diao, Hazell, & Thurlow 2010). Agricultural growth consistently has been shown to be more effective in reducing poverty than comparable growth in other economic sectors (Gollin et al. 2002; Irz & Tiffin 2006; Ravallion & Datt 1996). Its impact on poverty is both direct, flowing immediately from growth in agriculture by raising real incomes of poor farm (and nonfarm) households, and indirect, due to increasing agricultural output inducing job creation in upstream and downstream nonfarm sectors in response to higher domestic demand (Diao, Hazell, & Thurlow 2010; Christiaensen et al. 2011; Collier & Dercon 2014; Gollin et al. 2014).

Despite the important role and impacts of agricultural productivity growth on poverty reduction, the effects of climate change, including droughts, lower or erratic rainfall, and shorter rainy seasons, are adversely affecting agricultural production in Africa. Over the next decade, Africa could face a near double-digit percentage point reduction in crop yields and production volumes (Havlík et al. 2015). Although accurately predicting the effects of climate change on farming systems is difficult, the relevant literature suggests greater variability in agricultural production and a potential decline in crop productivity across SSA (Fisher et al. 2015; Rippke et al. 2016; Amare et al. 2018). More precisely, rainfall shocks have negatively affected inclusive growth in SSA, and, in particular, have harmed agricultural productivity, affecting consumption and increasing economic inequality between households and individuals (Belloumi 2014; Rippke et al. 2016). Agricultural productivity shocks are considered important determinants of rural income inequality, even though direct evidence to support this conclusion is relatively scarce.

That said, variability in agricultural productivity may not necessarily contribute to inequality if other factors can compensate for the economic difficulties it causes. For example, if labor, capital, and other factors are highly mobile, factor markets can help mitigate climate-induced agricultural productivity shocks on economic inequality across space. As the contributions of nonfarm economies rise in SSA countries, off-farm incomes increasingly may be able to mitigate the effects of agricultural productivity shocks, even among households (Oseni & Winters 2009; Dorosh and Thurlow 2016). Furthermore, informal risk-sharing and credit lending or borrowing practices common in rural Africa have mitigated some of the effects of limited access to formal sector financial markets. In such settings, whether and to what extent heterogeneity in agricultural productivity shocks contributes to consumption inequality becomes an important research question.[1]

To provide insights into this question, we use three-wave panel survey data from the Living Standards Measurement Study – Integrated Surveys on Agriculture (LSMS–ISA) for Nigeria and similar panel survey data from Uganda to examine the impact of agricultural productivity shocks on household consumption and inequality. By using two countries for which levels of inequality are higher than the average inequality for SSA countries, we provide insights on the impact of variability in agricultural productivity on consumption and inequality. Using georeferenced and nationally representative household panel data from the LSMS–ISA datasets for both countries, we merge these panel data with satellite-based long-term precipitation data. We use rainfall shocks as a proxy for estimating the exogenous variability in agricultural productivity that affects consumption. We believe that rainfall shocks are a suitable proxy to predict exogenous variability in agricultural productivity which affects consumption in both countries, as agricultural production activities in both are predominantly rainfed. We also exploit the panel data to explore the impact of variability in agricultural productivity on changes in consumption inequality over time.

We find that a negative rainfall shock decreases agricultural productivity by 7 percent in Nigeria and by 36 percent in Uganda. This is high but reflects the reliance of smallholder agriculture on seasonal rainfall in these countries. A 10 percent increase in the variability of agricultural productivity decreases household consumption by 37 and 52 percent on average for Nigeria and Uganda, respectively. Controlling for other factors, variability in agricultural productivity contributed to between 20 and 43 percent of consumption inequality in Nigeria from 2010 to 2015; and to between 16 and 31 percent of inequality in Uganda from 2009 to 2011. We also show that variability in agricultural productivity increases changes in consumption inequality over time and that agricultural productivity shocks accelerate changes in consumption inequality over time. In Nigeria, variability in agricultural productivity increased changes in consumption inequality by 35 percent between 2010 and 2015, while in Uganda variability in agricultural productivity increased change in consumption inequality by 29 percent between 2009 and 2011.

Our study contributes to the literature along several dimensions: First, it provides important insights into consumption inequality, a factor that has not been widely investigated. The existing literature often focuses on income inequality. This focus on consumption rather than on income is important because consumption is more directly linked to household utility. Consumption measured as expenditures, as in this case, tends to be a better indicator of true incomes as compared to reported incomes (Deaton 1995). The broader category of "income" may not necessarily capture the informal risk-sharing or credit markets that often mitigate the effects of income shocks on consumption.

Second, our study investigates the direct role of variability in agricultural productivity on consumption inequality. In explaining the key drivers of inequality, past studies have focused on many different elements, including resource endowments (land, capital), asset endowments, access to physical infrastructure (Jacoby 2000), financial markets, human capital, and access to health services (Binswanger & Deininger 1997). However, these factors are only indirectly associated with the heterogeneity in climate-induced agricultural productivity shocks. Consequently, a more direct evaluation of this variability in agricultural productivity is valuable.

Third, we use a fixed-effects instrumental variable (FE-IV) method by using rainfall shocks as a proxy for estimating the exogenous variability in agricultural productivity that affects consumption to mitigate the endogeneity attributable to both unobserved time-invariant and time-variant household

[1]We measure agricultural productivity through analysis of land productivity. We measure agricultural productivity as the real net crop income per hectare (ha). Net crop income is the cost of agricultural production and the proceeds from total value of harvest, from which we computed net crop income, which is calculated as gross crop income minus variable crop production costs.

fixed effects. This approach allows interesting cross-country analyses that offer insights on the impact of variability in agricultural productivity on consumption and inequality.

The remainder of the paper is organized as follows. Section 2 presents the conceptual and measurement issues on variability in agricultural productivity and consumption inequality. Section 3 discusses data issues and the key variables used for the analysis. Section 4 focuses on the empirical model and the identification strategy adopted. Section 5 presents the empirical results, followed by a concluding section that highlights our main findings and their policy implications.

2. CONCEPTUAL FRAMEWORK

In a perfect labor market setting, labor can move freely across locations or between sectors so that the marginal productivity of labor (of the same quality, e.g., equal characteristics, skill levels) is equalized across households. Similarly, with a perfect market for land, factors are allocated accordingly across locations so that the marginal productivity of land (of the same quality) is equalized across households. However, because developing countries like Nigeria and Uganda often have imperfect markets, households are subject to productivity differences in labor and land, with rainfall shocks causing persistent variations across households in terms of farm labor and land productivity. We may assume that the utility from consumption (including the discounted utility) is the same across households if the households have the same observed characteristics and the same degree of risk aversion. If local credit and insurance markets are perfect, variability in agricultural productivity should not affect households' consumption and inequality. In such a situation, households will transfer incomes across time and consume up to the level where their marginal utility of consumption equals the (shadow) current prices of goods; if the markets for consumption goods also are perfect, these levels should be equal across households. However, because countries like Nigeria and Uganda often have imperfect markets, farm variability in agricultural productivity translates into consumption change across households, even after controlling for their observed characteristics.

A large share of the SSA population lives in rural areas and depends on rainfed agriculture for their livelihoods – according to the World Bank (2014), more than 60 percent of the total labor force and more than 75 percent of the poor in SSA countries depend on agriculture for their livelihoods. With such a sizeable portion of the rural population involved in agriculture, raising the agricultural productivity of the poorest households, which typically have low productivity, is critical for reducing inequality among farmers (Datt & Ravallion 1998; Ravallion & Datt 1996; Christiaensen et al. 2011; Thirtle et al. 2003). At the same time, climate and other natural conditions in SSA countries are highly diverse and lead to a heterogeneity of livelihood strategies, with highly diversified subsistence agriculture in marginal and remote areas and input-intensive farming in more accessible regions (Jalan & Ravallion 2004). In such circumstances, resource-poor farmers bear the high cost of rainfall shocks and may find it difficult to adopt productivity-enhancing technologies and inputs or to diversify into high-value commodities (Shiferaw et al. 2015; Dercon & Christiaensen 2011; Hellmuth et al. 2009; Anderson & Feder 2007; Amare et al.,2012). Indeed, inequality may be aggravated if the improved productivity of wealthier farmers depresses local crop prices in ways that substantially reduce the agricultural incomes of poorer farmers (Collier & Dercon 2014; Dercon & Gollin 2014). Thus, the impact of variability in agricultural productivity on consumption inequality depends on households' risk-bearing capacities, level of market integration, level of assets, and perceptions of rainfall variability (Dercon & Christiaensen 2011).

For empirical purposes, we assess the effect of variability in agricultural productivity on household consumption and inequality by estimating the following: (1) the impact of rainfall shocks on variability in agricultural productivity, (2) the effect of variability in agricultural productivity on household consumption, and (3) the effect of variability in agricultural productivity on consumption inequality at a given point in time and on changes in consumption inequality over time.

3. DATA SOURCES AND KEY VARIABLES

We first discuss the data sources, descriptive results and the key variables used for the analysis. We then present an overview of rural consumption inequality in Nigeria and Uganda, respectively.

3.1. Data sources and descriptive results

The study uses high-quality panel household survey datasets from the Uganda and Nigeria LSMS–ISA, representing the years 2010/11, 2012/13, and 2015/16 for Nigeria, and 2009/10, 2010/11, and 2011/12 for Uganda. The LSMS–ISA datasets are nationally representative, and the significant uniformity in the survey instruments used for both countries offers a unique opportunity for cross-country comparison. These datasets include detailed information on demographic and household characteristics, household shocks, assets, agricultural production, nonfarm income and other sources of income, allocation of family labor, hiring of labor, access to services such as agricultural extension, and detailed data on aggregate annual consumption. The agriculture module, among others, contains information on agricultural and livestock production, farm technology, use of modern inputs, and productivity of crops and livestock.

The LSMS–ISA datasets include georeferenced information related to the households and plots surveyed that allow us to link any number of satellite-based precipitation datasets to sample households. We merge these panel data with satellite-based spatial data on precipitation. Long-term precipitation data came from the daily Africa Rainfall Climatology Version 2 (ARC2) of the National Oceanic and Atmospheric Administration's Climate Prediction Center (NOAA-CPC) summed by 10-day period and corrected for possible missing daily values (Novella & Thiaw 2013). Satellite-based long-term precipitation data is a better option than rain gauge measurements as satellite data are less likely to suffer from classical or nonclassical measurement errors caused by the sparseness and number of operating gauge stations (Macinni & Yang 2009; Brückner & Ciccone 2011; Björkman-Nyqvist 2013; Rocha & Soares 2015; Amare et al. 2018). The rainfall season typically extends from early May through late October for northern Nigeria and from early March through October for southern Nigeria. The annual rainfall pattern over much of Uganda is bimodal. For the analysis here, we considered rainfall over the period January through July.

We created a measure of rainfall anomalies during the rainy season by first calculating the average total rainfall across the rainy months for each country and georeferenced household for a 30-year period (e.g., Macinni & Yang 2009; Björkman-Nyqvist 2013; Rocha & Soares 2015; Amare et al. 2018). We then calculated z-scores for each year's rainy season rainfall based on deviations from the long-term mean. We construct rainfall shocks from standardized deviation of a given year's precipitation during the rainy season from historical averages using a standardized anomaly index (SAI) as a proxy for the exogenous variability in agricultural productivity. From the SAI, we construct a dummy variable designed to capture extreme events. A negative rainfall shock is a dummy variable used if the metrics indicate a level of rainfall that is one standard deviation below the long-term mean. A positive rainfall shock is a dummy variable used if the metrics indicate a level of rainfall that is one standard deviation above the long-term mean.

Since our objective is to explore how climate-induced variability in agricultural productivity will affect household consumption and inequality, we restrict the data to farm households that planted crops and for which data on rainfall is available at the household level. This procedure results in a balanced panel of 2,889 farm households for three waves of panel data in Nigeria and 1,750 farm households for three waves of panel data in Uganda. Our key variables of interest are rainfall shocks, variability in agricultural productivity, household consumption, and consumption inequality.

Table 1: Descriptive statistics of variables used in econometric analysis by country, pooled

Variable	NIGERIA Mean	NIGERIA Std. Dev.	UGANDA Mean	UGANDA Std. Dev.
Real consumption per adult equivalent (PPP USD)	1,174.55	1,968.14	561.39	724.72
Agricultural productivity – real net crop income per hectare (PPP USD)	3,441.39	7,582.58	1,956.43	3,726.62
Family size (adult equivalent)	5.19	2.55	6.64	3.00
Female headed household (female=1)	0.14	–	0.29	–
Educational attainment of household head (years)	5.79	5.63	2.12	3.94
Age of household head (years)	51.39	13.52	47.89	14.84
Own landholding size (ha)	0.41	9.06	1.06	1.48
Value of total assets (PPP USD)	589.01	1,209.27	2,293.32	3,092.38
Livestock owned (Tropical Livestock Units)	0.38	4.50	0.39	0.79
Real net agricultural income (PPP USD)	1,968.58	3,519.74	1,100.85	2,195.62
Real wage income (PPP USD)	338.37	7877.13	72.06	238.58
Real self-employment income (PPP USD)	700.05	8,945.81	145.74	431.74
Real remittances/transfers (PPP USD)	15.23	503.49	81.26	343.89
Total real income (PPP USD)	3,022.23	4,851.39	1,798.58	3,028.42
Fertilizer use (yes=1)	0.42	–	0.20	–
Pesticides and herbicides use (yes=1)	0.26	–	0.15	–
Access to extension (yes=1)	0.08	–	0.11	–
Access to finance (yes=1)	0.01	–	0.04	–
Distance to all-weather road (kilometers)	10.54	13.40	8.11	7.31
Rainfall deviation from mean – standardized score of deviation from long-term mean	0.29	0.81	0.12	1.55
Negative rainfall shock (NRS=1): level of rainfall at least one standard deviation below long-term mean	0.19	0.48	0.37	0.48
Positive rainfall shock (PRS=1): level of rainfall at least one standard deviation above long-term mean	0.18	0.40	0.44	0.50
Observations	8,667		5,250	

Source: Based on LSMS–ISA surveys in Nigeria and Uganda.
Note: Household consumption, income, and asset measures are computed in purchasing power parity adjusted U.S. dollars (PPP USD).

Table 1 reports the mean values for agricultural productivity; household consumption; net real income;[2] demographic characteristics; wealth indicators, which include land, livestock, and the value of total assets; and rainfall shocks. We measure consumption and wealth indicators using real purchasing power parity (PPP) adjusted U.S. dollars (USD), with the regional consumer price index reflecting 2010 PPP and per adult equivalent unit (AEU). The average pooled survey consumption per AEU in PPP is USD 1,175 in Nigeria and USD 561 in Uganda. The average agricultural productivity, measured in term of net crop income per hectare (ha), is USD 3,441 per ha in Nigeria and USD 2,033 per ha in Uganda. Table 1 also reports descriptive results on community characteristics and access to extension, infrastructure, financial institutions, and information.

3.2. Overview of rural consumption inequality

This sub-section presents an overview of the consumption inequality measured in consumption per AEU for both countries. Table 2 reports some preliminary findings about potential correlations between land productivity and household income by income quintiles. The results indicate that

[2] Net real income is computed from net agricultural returns to land and family labor, household income from nonfarm income (both nonfarm wage and nonfarm self-employment), and remittances adjusted using the regional consumer price index to 2010 purchasing power parity (PPP).

average income correlates with average agricultural productivity. Households with the highest incomes have higher agricultural productivity in both countries.

Table 2: Agricultural productivity by household income quintile, real net crop income per hectare, PPP USD

Income quintile	NIGERIA Observations	NIGERIA Mean	NIGERIA Std. Dev.	UGANDA Observations	UGANDA Mean	UGANDA Std. Dev.
Poorest	1,733	699	1,328	1,050	1,655	3,277
2	1,733	2,242	5,830	1,050	1,687	3,112
3	1,734	3,234	7,056	1,050	1,999	3,783
4	1,733	4,196	8,207	1,050	2,052	3,939
Wealthiest	1,734	6,971	10,488	1,050	2,344	4,386

Source: Based on LSMS–ISA surveys in Nigeria and Uganda.
Note: PPP USD = purchasing power parity adjusted U.S. dollars.

Table 3 presents consumption per AEU and the percentage annual change in mean consumption by quintile for both countries and for each survey year. Although mean consumption for both the bottom and top quintile households in Nigeria increased significantly, the top quintile households experienced substantially higher mean consumption growth rate – 5 percent per year, as compared to 0.7 percent annually for bottom quintile households during the period 2010 to 2015. For Uganda, the results indicate that mean consumption declined for bottom quintile households during the period 2009 to 2011, whereas mean consumption for top quintile households grew significantly by 1.5 percent per year during the same period.

Table 3: Real consumption per adult equivalent by household consumption quintile in Nigeria and Uganda, PPP USD

NIGERIA	Pooled	2010	2012	2015	Annualized percentage change in mean (2010–2015)
Poorest	365	354	377	366	0.67***
2	620	620	624	616	-0.10
3	869	875	867	867	-0.20
4	1,215	1,217	1,209	1,221	0.07
Wealthiest	2,803	2,252	3,230	3,002	4.99***
Observations	8,667	2,889	2,889	2,889	
UGANDA	**Total**	**2009**	**2010**	**2011**	**Annualized percentage change in mean (2009–2011)**
Poorest	171	182	170	178	-0.45
2	288	294	286	287	-0.48***
3	414	418	414	409	-0.44
4	603	610	593	601	-0.30
Wealthiest	1,332	1,298	1,342	1,401	1.47***
Observations	5,250	1,750	1,750	1,750	

Source: Based on LSMS–ISA surveys in Nigeria and Uganda.
Note: Standard errors, clustered at the enumeration area, are given in parentheses. *** p<0.01. ** p<0.05. * p<0.10.
PPP USD = purchasing power parity adjusted U.S. dollars.

Table 4 summarizes estimates of inequality for both countries. To provide a complete ordering of distributions and to assess the robustness of trends observed, we report consumption inequality using several indices. These include percentile ratios, generalized entropy (GE) indices, and the Gini coefficient for 2010, 2012, and 2015 for Nigeria and for 2009, 2010, and 2011 for Uganda.

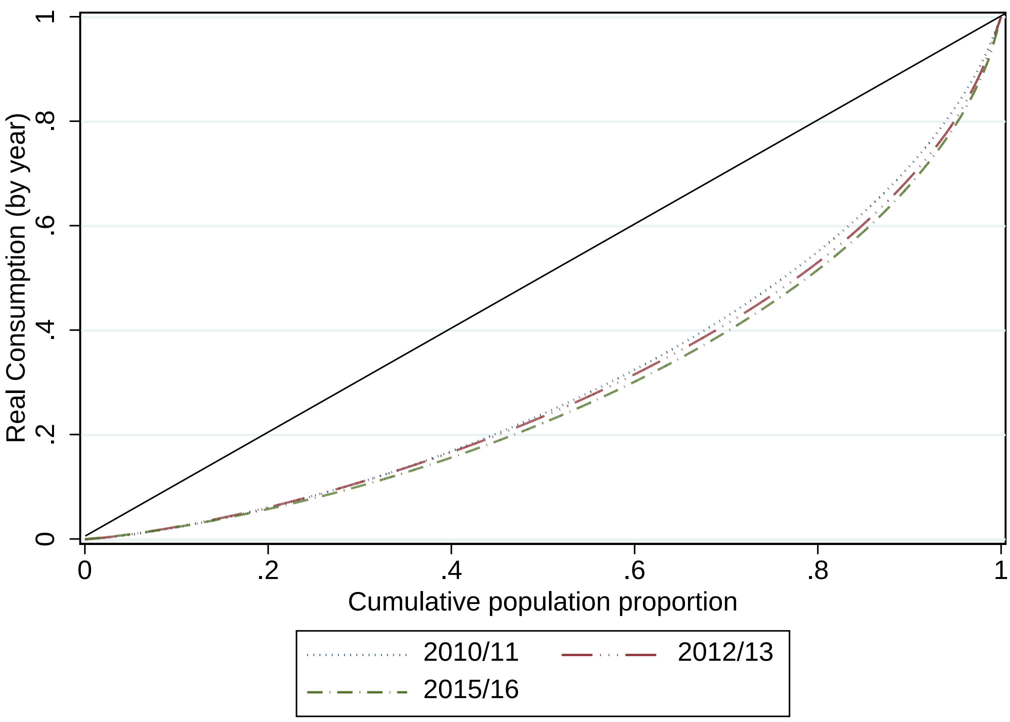
Table 4: Level and trends of consumption inequality in Nigeria and Uganda by different inequality measures

	NIGERIA						UGANDA					
				Change (%) annualized						Change (%) annualized		
	2010	2012	2015	2010-12	2012-15	2010-15	2009	2010	2011	2009-10	2010-11	2009-11
p90/p10	6.21	6.09	6.65	-0.94	3.08	1.43	5.08	6.16	5.63	21.20	-8.62	5.38
p90/p50	2.48	2.62	2.78	2.79	2.14	2.47	2.36	2.65	2.60	12.37	-2.11	5.00
p10/p50	0.40	0.43	0.42	3.76	-0.86	0.95	0.46	0.43	0.46	-7.33	7.21	-0.32
p75/p25	2.57	2.49	2.67	-1.59	2.37	0.74	2.33	2.50	2.44	7.04	-2.40	2.23
p75/p50	1.60	1.61	1.65	0.28	0.85	0.63	1.53	1.57	1.62	2.61	3.18	2.94
p25/p50	0.62	0.65	0.62	1.93	-1.45	-0.13	0.66	0.63	0.67	-4.10	5.55	0.61
GE(0)	0.26	0.39	0.34	24.01	-3.97	6.07	0.26	0.31	0.57	21.23	82.49	60.62
GE(1)	0.26	0.58	0.41	61.71	-9.78	11.58	0.32	0.38	0.70	19.02	84.02	59.51
GE(2)	0.34	2.90	1.07	371.75	-21.05	42.18	0.70	0.79	1.49	13.02	88.48	56.51
Gini	0.39	0.47	0.45	10.98	-1.77	3.10	0.53	0.60	0.56	13.75	-7.62	2.54

Source: Based on LSMS–ISA surveys in Nigeria and Uganda.
Note: p90 stands for the 90th percentile of the consumption distribution and similarly, p10, p50, p75 and p25. The inequality measures are defined as:
$Gini = \frac{-(n+1)}{n} + \frac{2}{n^2\mu_c}\sum_{i=1}^{n} ic_i$; $GE(0) = \frac{1}{n}\sum_{i=1}^{n} \ln\left(\frac{c_i}{\mu_c}\right)$; $GE(1) = \frac{1}{n}\sum_{i=1}^{n} \frac{c_i}{\mu_c}\ln\left(\frac{c_i}{\mu_c}\right)$; and $GE(2) = \frac{1}{2n{\mu_c}^2}\sum_{i=1}^{n}(c_i - \mu_c)^2$.

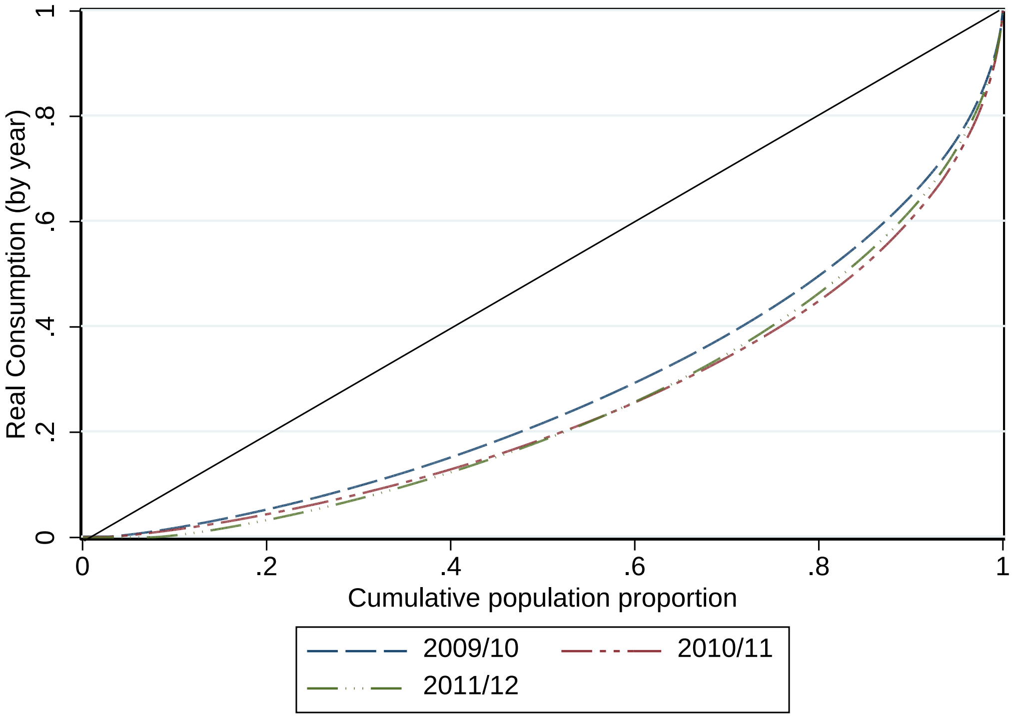
The results show an increase in inequality for both countries over the respective periods across almost all inequality measures. Inequality of consumption increased in both countries, especially for consumption in the upper tail of the consumption distribution, as GE (2) shows. Although inequality of consumption increased in both countries, it remained consistently lower in Nigeria than in Uganda. Based on the Gini index, consumption inequality in Nigeria grew by 3.1 percent per year from 2010 to 2015, while in Uganda it grew by 2.5 percent per year from 2009 to 2011.

Figure 1: Lorenz curves for household consumption in Nigeria, by year



Source: Based on LSMS–ISA surveys in Nigeria.

Figure 2: Lorenz curves for household consumption in Uganda, by year



Source: Based on LSMS–ISA surveys in Uganda.

The rise in consumption inequality over the reference periods in both countries also can be seen in the outward shifts and increase in overall consumption inequality in the Lorenz curves in Figures 1 and 2.[3] A possible explanation for the rising consumption Gini coefficients are barriers to participation in high-return activities by households in the middle and lower consumption quintiles that make it difficult for these households to accumulate assets.

The next section examines the factors that contributed to increasing consumption inequality over the period using both a conventional decomposition and a regression-based inequality decomposition approach (Cowell and Fiorio 2011).

4. EMPIRICAL STRATEGIES AND IDENTIFICATION

Here, we first discuss the empirical approach used to estimate the impact of variability in agricultural productivity on household consumption, while in the second section we present both a conventional decomposition and a regression-based inequality decomposition approach.

4.1. Variability in agricultural productivity and household consumption

In our empirical approach to estimating the impact of variability in agricultural productivity on household consumption and inequality, we follow previous research to guide our choice of control variables (e.g., Dercon & Christiaensen 2011). Building on the previous section and the research literature, we estimate the impact of agricultural productivity change on household consumption using the following consumption function:

$$ln\,(C_{it}) = \gamma_1 ln\,(Y_{it}) + \beta_x ln(X_{it}) + \varsigma_i + \eta_{it} \quad (1)$$

[3] The Lorenz curve represents the functional relationship between the cumulative proportion of consumption and the cumulative proportion of expenditure units, assuming that consumption units are arranged in ascending order of consumption.

where $\ln(C_{it})$ is household consumption measured by the natural logarithm of the real value of household consumption per AEU. Y_{it} captures agricultural productivity measured as real net crop income per ha on the farm. This variable is expected to have a positive effect on consumption. Only downside variability can have a negative effect. X_{it} is a vector of farm and household characteristics, including household size; sex, education, and age of household head; landholding size, assets, and livestock; and income from wages, self-employment, and transfers at household level (i) in year t. Because similar intrinsic demographic characteristics can lead to different asset distribution patterns, a household fixed effect, ς_i, is included to control for time-invariant unobserved household characteristics. η_{it} is the error term, for which the strict exogeneity condition is assumed to hold. It is independently and normally distributed with zero mean but potentially heteroskedastic.

However, agricultural productivity is endogenous and can be expected to be simultaneously determined with household consumption. Agricultural productivity also is expected to be correlated with unobserved heterogeneities (unobserved variation in plot characteristics, managerial skills, or ability), which may affect household consumption. Thus, an ordinary least squares (OLS) estimation of equation (1) may produce biased estimates of variables of interest, such as variability in agricultural productivity (Angrist & Evans 1998).

To address this, we apply a fixed-effects instrumental variable (FE-IV) approach to identify the exogenous component of variability heterogeneity in agricultural productivity. The idea is to find the part of agricultural productivity affected only by weather shocks and thus embodies only exogenous variation in agricultural productivity which affects consumption. In regions where a large share of the population lives in rural areas and depends on rainfed agriculture for their livelihoods, deviation of rainfall from the long-term mean in respective survey years has a marked impact on the livelihoods of farmers and can be a plausible instrument for predicting agricultural income growth. We follow a similar procedure and constructed rainfall shocks from the standardized deviation of a given year's precipitation during the rainy season from long-term averages using a standardized anomaly index (SAI). We complement the household FE estimates with an IV regression to control endogeneity related to unobserved heterogeneities. Other studies seeking to exploit some exogenous variation in agricultural productivity also have proposed instruments constructed from historical rainfall data (Macinni & Yang 2009; Brückner and Ciccone 2011; Björkman-Nyqvist 2013; Rocha & Soares 2015; Amare et al. 2018).[4]

We exploit the exogenous variation in agricultural productivity generated by the rainfall shocks and estimate the following two-stage FE-IV approach:

$$ln\,(Y_{it}) = \beta_0 + \beta_1 ln(X_{it}) + \beta_3 W_{it} + \nu_i + \varepsilon_{it} \tag{2}$$

$$ln\,(C_{it}) = \gamma_0 + \gamma_1 ln\,(\hat{Y}_{it}) + \gamma_2 ln(X_{it}) + \varsigma_i + \eta_{it} \tag{3}$$

where equation (2) is the first-stage regression and equation (3) is the second-stage regression. W_{it} is a vector of negative and positive rainfall shocks at household level (i) in year t. ν_i stands for the inclusion of household fixed effects in the first stage. $\hat{Y}_{it}$ is the predicted value of the climate-induced variability in agricultural productivity proxied using the standardized rainfall deviations W_{it}.[5] Other notations are similar to those in equation (1).

[4] The alternative approach is to use the Chamberlin correlated random effect estimator. However, in the recent literature (e.g., Ricker-Gilbert et al. 2011; Takeshima & Nkonya 2014), the Chamberlin correlated random effect estimator has been used more in the models dealing with binary or censored dependent variables, for which standard FE methods are infeasible or lead to inconsistent results due to incidental parameter problems. In our case, this issue is of less concern since our dependent variables are continuous, non-censored variables. In addition, our analyses focus on the effects of time-variant covariates and do not require information regarding coefficients on time-invariant covariates.

[5] $\hat{Y}_{it}$ can be interpreted as "the predicted value of the climate-induced variability in agricultural productivity" proxied (or is this instrumented) using the standardized rainfall deviations W_{it}. Note that Y_{it} is the agricultural productivity measured as real net crop

One concern about the validity of our instruments is that rainfall shocks also could affect non-farm activities and be correlated with non-farm activities and local prices, which may directly affect households' consumption. To minimize this problem, we control for household income from non-farm activities, household wealth indicators, and community variables in both equations. We also use real values (using the regional consumer price index) of all income sources, as these values can control the price effect of rainfall on our key dependent variable. Thus, we assume here that after we control for a wide range of household variables, rainfall shocks influence consumption indirectly via agricultural productivity.

4.2. Variability in agricultural productivity and consumption inequality

After identifying the impact of climate-induced variability in agricultural productivity on household consumption, we employ both a conventional decomposition and a regression-based inequality decomposition analysis to explore the impact of variability in agricultural productivity on consumption inequality. Specifically, we investigate the impact of variability in agricultural productivity on consumption inequality at a given point in time and changes in inequality to investigate possible changes over time.

The conventional approach to inequality decomposition typically decomposes the total inequality by either population groups or factor components, both of which provide limited information on the determinants of consumption inequality. Moreover, these approaches are unable to control for other factors when trying to identify and measure the contribution of a particular variable (Cowell and Fiorio 2011; Naschold 2009; Bourguignon et al. 2001; Shorrocks 1999; Fields 2003). Recent applied work has reawakened interest in inequality decomposition by focusing on the use of regression-based approaches to avoid some of the restrictions of the traditional methods (Oaxaca 1973; Blinder 1973; Juhn et al. 1993; Bourguignon et al. 2001). We first use regression-based decomposition to investigate the impact of variability in agricultural productivity on consumption inequality at a given point in time. Second, we use regression-based decomposition to examine the impact of variability in agricultural productivity on changes in consumption inequality over time.

Regression-based inequality decomposition methods also allow for quantification of the effects of variables on consumption inequality and enable the inclusion of factors that may drive the observed inequality, such as demographic variables, wealth indicators, and access to credit and input use (Halvarsson et al. 2018; Brewer and Wren-Lewis 2016; Cowell and Fiorio 2011). We adopt the Fields decomposition method (Fields 2003) to identify the impact of variability in agricultural productivity on consumption inequality after controlling for other factors. This method yields an exact additive decomposition of any inequality measure into its contributory factors. Indeed, the decomposition of a given inequality measure through a regression-based method, combined with the Fields approach, assesses the contributions of our main interest variables and a set of other factors, the sum of which accounts for the inequality indicator. Nevertheless, the Fields method has some limitations. For example, the functional form for the income-generating function must be log-linear. However, given that our model is log-linear, this is not a major limitation for our analysis.

Using the Fields method, we begin with the consumption function specified in equation (2). The explanatory variables include variability in agricultural productivity, household demographic and wealth indicators, and access to credit and input use. The results of the estimation of the determinants of household consumption function are then used to disentangle the contribution of variability in agricultural productivity and other factors to consumption inequality.

income per ha on the farm. Depending on negative or positive deviations in year t, the predicted value would be the projected real net crop income under that weather outcome.

The contribution of the independent variables to distributional change is then expressed as a function of the size of the coefficients of the consumption equation and the magnitude of the change in the variable relative to the variation in consumption inequality. This allows us to estimate the percentage contribution of the flow of consumption inequality accounted for by explanatory variables (z_k) (which contain $\mathrm{Y, X, and\ H}$) to consumption inequality, using the following relative factor inequality weight (k) identity:

$$\sigma_C^2 = \sum_{k=1}^{k-1} \sigma_{\gamma_k z_k, C} + \sigma_{\eta, C} \tag{4}$$

where σ_C^2, $\sigma_{\gamma_k z_k, C}$, and $\sigma_{\eta, C}$ are the variance of the log-consumption indicator, the covariance of $\gamma_k z_k$ and *C*, and the covariance of the residuals (η) and *C*, respectively. Empirically, the relative factor inequality weight for factor k using the OLS estimate of the coefficient of the determinants of the consumption function is given as:

$$s_k = \frac{\sigma_{\gamma_k z_k, C}}{\sigma_C^2} = \frac{\gamma_k \cdot \sigma_{xk} \cdot \sigma_{xk,C}}{\sigma_y} \tag{5}$$

The term s_k is also known as the "factor inequality weight." The sign of s_k indicates whether the income flow from z_k is inequality increasing or decreasing. If $s_k = 0$, the consumption inequality from factor k is as equal or as unequal as the total consumption inequality. As a result, factor k has no impact on total inequality.[6] The regression error shows how much of total consumption inequality remains unaccounted for by the income flows from endowments denoted by the explanatory variables. Fields (2003) argues that the relative contribution of a factor to overall inequality is invariant to the choice of inequality measure under six axioms proposed by Shorrocks (1982). Hence, the contribution of an individual factor to consumption inequality is simply $s_k \cdot C$. The residuals are treated as another factor whose coefficient is one ($\gamma_k = 1$). Factors are composed of residuals (K-th factor) and (K - 1) exogenous variables, excluding the constant in equation (5).

Accordingly, given that our fourth objective is to investigate the impact of variability in agricultural productivity on the change in consumption inequality, we use the Fields method (Fields 2003) to calculate the contribution of z_k to the total change in consumption inequality between time periods. The key advantage in using multiple rounds of panel data is that it makes it easy to examine the impact of variability in agricultural productivity on changes in consumption inequality over time by looking at changes in inequality caused by changes in returns to factors and in the distribution of these factors. Using the variance of the log of household consumption, σ_y, to measure inequality, the contribution of z_k to the change in consumption inequality between two periods, T_0 and T_1, is expressed as:

$$\pi_k = \frac{s_{kT_1}\sigma_{CT_1}^2 - s_{kT_0}\sigma_{CT_0}^2}{\sigma_{CT_1}^2 - \sigma_{CT_0}^2} \tag{6}$$

in which additional subscripts T_1 and T_0 indicate the values of s_k and σ_C^2, respectively.

5. RESULTS AND DISCUSSION

We first generated the first stage estimates of the impacts of rainfall shocks on agricultural productivity shocks using the FE model (not shown). The results of this first-stage estimation are mainly used in the later FE-IV analysis to explain household consumption and inequality. We find

[6] The contribution of *k* to inequality in C largely depends on distributions of k in the sample – specifically, the similarity of the distribution of k with the distribution of C. The contribution of *k* to inequality in C likewise depends on the coefficients γ_k, which is the effect of a marginal change of *k* on the expected value of *C*, conditional on the values of all other k. γ_k is assumed to be the same for all farm households in the sample. Thus, s_k is largely positive (negative) if *k* and *C* are positively (negatively) correlated and γ_k is positive (negative); and s_k is largely negative (positive) if k and *C* are positively (negatively) correlated and γ_k is negative (positive).

that a negative rainfall shock decreases agricultural productivity by 7 and by 36 percent in Nigeria and Uganda, respectively. This is because the negative rainfall shock directly reduces productivity owing to moisture stress on the crop. In addition, it could pose a crop production risk, which affects behavior in terms of farm technology adoption and, thus, reduces production and productivity in non-irrigated smallholder systems (Amare and Shiferaw 2017; Dercon & Christiaensen 2011).

5.1. Impact of variability in agricultural productivity on consumption

Table 5 presents the estimation results regarding the impact of variability in agricultural productivity on consumption using the FE-IV model for Nigeria and Uganda. To conduct causal inference on the impact of variability in agricultural productivity on consumption and inequality, we need to confirm the relevant and the validity-identifying assumptions of the instrument. The rainfall shocks and joint significance test for negative and positive shocks have a statistically significant (at 1 percent) impact on agricultural productivity, which indicates that rainfall shocks predict variability in agricultural productivity in both countries. We also check the validity of instruments using two major misspecification tests: the weak identification test and the overidentification tests. The Sargan–Hansen test is used to test overidentifying restrictions; it fails to reject the joint null hypothesis that our instruments are valid. We also apply the Hansen specification test for the endogeneity of agricultural productivity and reject the null hypothesis that agricultural productivity can be treated as exogenous. In addition, we computed robust standard errors to correct for potential heteroskedasticity.

Table 5: Impact of variability in agricultural productivity on consumption, fixed-effects instrumental variable (FE-IV) estimates

Dependent variable: Consumption per adult equivalent	NIGERIA		UGANDA	
Variability in agricultural productivity	-0.373**	(0.156)	-0.520***	(0.106)
Family size	-0.059***	(0.015)	-0.200*	(0.111)
Female HH head	0.067**	(0.028)	-0.081	(0.115)
Education of HH head	0.020**	(0.009)	0.027	(0.025)
Age of HH head	-0.065**	(0.027)	-0.022	(0.109)
Farm size	-0.695*	(0.415)	0.062	(0.043)
Livestock	0.111***	(0.035)	0.244***	(0.081)
Value of total assets	0.102**	(0.041)	0.053***	(0.014)
Wage income	0.012***	(0.004)	-0.010	(0.011)
Self-employment income	0.135***	(0.010)	0.017*	(0.009)
Transfer	0.019*	(0.011)	0.027***	(0.010)
Credit use	-0.044	(0.078)	-0.132	(0.089)
Distance to road	0.008	(0.011)	-0.191	(0.141)
Fertilizer	-0.030	(0.028)	0.177***	(0.059)
Pesticides/herbicides	0.133***	(0.022)	0.179***	(0.067)
Extension	0.046	(0.029)	0.064	(0.061)
Constant	6.682***	(0.198)	9.495***	(0.758)
Over identification test of all instruments (Hansen J statistics): $\chi 2$	11.37***		190.43***	
Weak-instrument-robust inference (Stock-Wright LM S statistic)	27.52***		178.52***	
Endogeneity test	5.75**		37.51***	
F-test of excluded instruments	5.68***		85.20***	
Observations	8,667		5,250	

Source: Based on LSMS–ISA surveys in Nigeria and Uganda.
Note: All continuous variables are given in log form. All wealth indicator variables are given in AEU terms. Standard errors, clustered at the enumeration area, are given in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01.

The estimates confirm that variability in agricultural productivity has a significant and negative impact on per capita consumption for both countries. Controlling for other factors, we find that in Nigeria a 10 percent increase in the levels of rainfall-induced agricultural productivity shocks decreases consumption by 37 percent on average. For Uganda, a 10 percent increase in rainfall-induced agricultural productivity shocks decreases consumption by 52 percent on average. Similarly, several regression coefficients are statistically significant, and the signs of the estimated coefficients are in line with theoretical expectations. Households with higher livestock, value of assets, wages, and non-farm income experience significantly higher per capita household consumption in both countries.

5.2. Impact of variability in agricultural productivity on consumption inequality

It has been argued in the relevant literature that additional insights can be gained by using a conventional decomposition alongside regression-based 'explanatory model' decompositions (e.g., Halvarsson et al. 2018; Brewer and Wren-Lewis 2016; Cowell and Fiorio 2011). Along these lines, we use two different decompositions in order to analyze changes in consumption inequality in Nigeria and Uganda by subgroup and by using a multivariate regression-based approach. We use both approaches because each one provides different insights into what drives inequality. Following these earlier studies, we first split the sample into two groups: a low agricultural productivity change group and a high agricultural productivity change group to investigate the role of agricultural productivity change on consumption inequality using a decomposition analysis.[7] This allows us to see how inequalities in consumption are related to agricultural productivity inequality and which subgroups of the population are affected most by agricultural productivity change inequality.

Table 6: Subgroup inequality decomposition by agricultural productivity change

NIGERIA	2010			2012			2015		
	GE(0)	GE(1)	GE(2)	GE(0)	GE(1)	GE(2)	GE(0)	GE(1)	GE(2)
High agricultural productivity	0.258	0.254	0.326	0.377	0.555	2.911	0.333	0.391	1.006
Low agricultural productivity	0.219	0.215	0.269	0.360	0.581	2.543	0.280	0.360	0.889
Within	0.238	0.239	0.322	0.368	0.566	2.885	0.307	0.379	1.038
Between	0.022	0.022	0.022	0.017	0.017	0.017	0.033	0.032	0.032
Total inequality	0.260	0.261	0.344	0.385	0.582	2.902	0.339	0.412	1.069
UGANDA	**2009**			**2010**			**2011**		
	GE(0)	GE(1)	GE(2)	GE(0)	GE(1)	GE(2)	GE(0)	GE(1)	GE(2)
High agricultural productivity	0.272	0.322	0.597	0.343	0.408	0.818	0.284	0.322	0.529
Low agricultural productivity	0.231	0.269	0.478	0.286	0.348	0.768	0.283	0.349	0.712
Within	0.259	0.317	0.701	0.313	0.377	0.792	0.284	0.336	0.638
Between	0.000	0.000	0.000	0.001	0.001	0.001	0.003	0.003	0.003
Total inequality	0.259	0.317	0.701	0.314	0.378	0.793	0.286	0.339	0.640

Source: Based on LSMS–ISA surveys in Nigeria and Uganda.

Table 6 presents the measures of inequality computed in each low and high agricultural productivity change group. It also shows the within and between subgroup decomposition of inequality for the three GE indices by low and high agricultural productivity change group for both countries in each period. The results show that both the inequality within agricultural productivity change subgroups and the inequality between groups increased in each country. The largest share of inequality comes from the high agricultural productivity change group for the three GE indices for

[7] We first split the sample into two groups based on the median of agricultural productivity change, a low agricultural productivity group defined if agricultural productivity change is below the median of agricultural productivity change and a high agricultural productivity change group if agricultural productivity change is above the median of agricultural productivity change.

both countries. Furthermore, it is the within-inequality component of each group that accounts for more than 90 percent of total inequality for Nigeria, and for almost all of the total inequality for Uganda. Looking at GE(0) within-group, inequality increases by 29 and by 6 percent per year from 2010 to 2012 and from 2010 to 2015, respectively, for Nigeria, and by 28 and by 4.5 percent per year from 2009 to 2010 and from 2009 to 2011, respectively, for Uganda. We stress, however, that a conventional decomposition provides limited information on the determinants of consumption inequality. Moreover, this approach is unable to control for other factors when trying to identify and measure the contribution of a particular variable.

We use the consumption function regression results to calculate consumption inequality and estimate the impact of variability in agricultural productivity on consumption inequality using the Fields method decomposition procedure.[8] Consumption inequality is decomposed into key components, such as variability in agricultural productivity, demographic, wealth indicators, and access to credit and input use. The two following sub-sections present the impact of variability in agricultural productivity on consumption inequality at a given point in time and on its changes over time for both countries.

5.2.1. Impact of variability in agricultural productivity on inequality at a given point in time

Table 7 presents the results from the decomposition procedures for consumption inequality in terms of the percentage share of total inequality explained by each factor and year for Nigeria and Uganda. The results indicate that consumption inequality increases with variability in agricultural productivity for both countries, albeit at different levels.

For Nigeria, controlling for other factors, variability in agricultural productivity contributed an estimated 43, 20, and 33 percent to consumption inequality in 2010, 2012, and 2015, respectively. The major economic crisis that started with the collapse of oil prices in 2014 and youth restiveness caused by natural and oil related shocks may account for much of the balance of the factors contributing to consumption inequality over these years (Arndt et al. 2018).

Turning to Uganda, after controlling for other factors, variability in agricultural productivity contributed an estimated 25, 16, and 32 percent of consumption inequality in 2009, 2010, and 2011, respectively. In other words, variability in agricultural productivity in Uganda added 25, 16, and 32 percent more to consumption inequality in 2009, 2010 and 2011, respectively.

We also find that wealth variables account for the largest share of total inequality for both countries. Wealth variables contributed about 17 and 47 percent of the consumption inequality in Nigeria 2010 and 2015, respectively, and 87 and 79 percent in Uganda in 2009 and 2011, respectively. Demographic characteristics and access to credit and input also play significant roles in explaining consumption inequality in both countries.

[8] Our analyses focus on the deterministic components of consumption inequality and do not consider that the consumption is further affected by purely idiosyncratic shocks or residual parts (the term ηit). Therefore, the shares add up to 100.

Table 7: Impact of variability in agricultural productivity on consumption inequality at a given point in time

Percentage share of change in consumption inequality explained by each factor						
	NIGERIA			UGANDA		
Factors	2010	2012	2015	2009	2010	2011
Variability in agricultural productivity	**42.94**	**19.90**	**32.95**	**24.76**	**15.74**	**31.29**
Demographic characteristics						
Family size	17.49	6.13	1.99	3.95	-0.42	1.97
Female HH head	1.18	-1.18	-0.27	-0.01	-0.03	0.00
Education of HH head	4.44	1.98	1.30	-2.96	0.60	-3.34
Age of HH head	-0.12	-0.04	0.09	-1.58	-1.06	-0.47
Total	**22.99**	**6.88**	**3.11**	**-0.60**	**-0.91**	**-1.84**
Wealth indicators						
Farm size	-20.85	-58.45	-11.26	11.93	11.05	18.29
Livestock	-0.07	0.37	-0.17	6.61	7.08	5.41
Value of total assets	-0.64	94.74	3.75	43.01	36.60	27.47
Wage income	4.22	5.00	0.48	8.04	15.70	10.77
Self-employment income	33.91	17.36	53.84	3.84	7.29	8.06
Transfer	0.71	0.98	0.22	13.47	13.01	8.51
Total	**17.28**	**60.00**	**46.85**	**86.89**	**90.73**	**78.51**
Input credit and input use						
Access to credit	-0.02	0.25	0.07	2.47	1.22	0.61
Use fertilizer	-0.08	1.47	1.06	-6.18	-4.71	-5.15
Use pesticides/herbicides	12.13	9.07	10.75	-0.75	-1.11	-0.46
Access to extension	0.66	0.01	1.94	-4.69	-1.53	-2.20
Distance to road	4.09	2.40	3.28	-1.89	0.57	-0.75
Total	**16.78**	**13.20**	**17.09**	**-11.05**	**-5.56**	**-7.96**

Source: Based on LSMS–ISA surveys in Nigeria and Uganda.

5.2.2. Impact of variability in agricultural productivity on the change over time in inequality

Table 8 shows the impact of variability in agricultural productivity and other factors on the change of inequality between the years.[9] A positive coefficient indicates that a factor helped increase inequality, while a negative coefficient indicates that a factor helped decrease inequality. Variability in agricultural productivity contributed to increases in inequality over time in both countries.

For Nigeria, variability in agricultural productivity increases the change in consumption inequality by 12, 5, and 36 percent for the periods 2010/11 to 2012/13, 2012/13 to 2015/16, and 2010/11 to 2015/16, respectively. For Uganda, variability in agricultural productivity increases the change in consumption inequality by 3, 13, and 29 percent between 2009/10 and 2010/11, between 2010/11 and 2011/12, and between 2009/10 and 2011/12, respectively. Wealth variables account for the largest share of increase in consumption inequality over time for both countries. Demographic characteristics, along with access to credit and inputs, also played significant roles in increasing consumption inequality over time in both countries.

[9] The table indicates the change in the variance of the log of consumption between 2010/11, 2012/13, and 2015/16 for Nigeria and between 2009/10, 2010/11, and 2011/12 for Uganda.

Table 8: Impact of variability in agricultural productivity on consumption inequality over time

Percentage share of change in consumption inequality explained by each factor						
	NIGERIA			UGANDA		
Factors	2010–12	2012–15	2010–15	2009-10	2010–11	2009-11
Variability in agricultural productivity	**12.16**	**5.39**	**35.73**	**3.28**	**13.23**	**29.26**
Demographic characteristics						
Family size	0.93	9.99	15.98	19.21	-0.40	-5.96
Female HH head	1.32	2.09	0.83	-0.25	-0.12	0.01
Education of HH head	2.74	1.21	-0.01	-1.12	0.02	1.30
Age of HH head	0.00	11.13	0.67	1.51	1.70	2.56
TOTAL	**4.99**	**24.42**	**17.46**	**19.35**	**1.20**	**-2.09**
Wealth indicators						
Farm size	4.96	19.29	20.24	5.72	12.33	5.05
Livestock	1.43	25.60	0.28	11.09	12.99	3.57
Value of total assets	6.67	-0.42	15.93	53.47	33.77	60.87
Wage income	7.67	0.77	1.72	-0.88	12.63	2.40
Self-employment income	31.62	4.88	3.24	-0.07	8.41	-0.08
Transfer	-0.05	0.02	-0.01	2.62	6.93	1.73
TOTAL	**52.30**	**50.14**	**40.61**	**71.95**	**87.06**	**73.54**
Input credit and input use						
Access to credit	0.12	-0.04	0.77	-0.69	1.07	3.17
Use fertilizer	3.22	5.21	2.57	0.74	3.74	-8.11
Use pesticides/herbicides	14.50	8.29	1.00	3.02	-2.08	0.77
Access to extension	2.50	-0.34	1.20	-1.97	-4.47	1.50
Distance to road	6.22	6.92	-0.08	4.32	0.25	1.96
TOTAL	**26.55**	**20.04**	**5.45**	**5.42**	**-1.50**	**-0.71**

Source: Based on LSMS–ISA surveys in Nigeria and Uganda.

In sum, the results show that variability in agricultural productivity can have differing impacts on different segments of the population. Agricultural productivity shocks increase consumption inequality both at a given point in time and worsen consumption inequality over time. This is mainly because in rainfed farming systems that lack water storage and irrigation investments for buffering the effect of drought and moisture stress, small-scale farmers with limited coping capacity to smooth consumption will, in particular, bear high costs from negative rainfall shocks. Negative rainfall shocks also can limit the uptake of new farm technology and push poor households to take on low-risk, low-return activities (Dercon & Christiaensen 2011; Alem et al. 2010; Shiferaw et al. 2015). The policy implication of this finding is to reduce the variability in agricultural productivity resulting from rainfall and other climate shocks.

The results show that wealth variables account for the largest share of changes that increase consumption inequality at a given point in time and over time for both countries. This finding is in line with the empirical findings of Anderson and McKay (2004), who found that around 50 percent of Africa's high consumption inequality could be attributed to inequality in key factor endowments, such as land and physical assets. In the presence of incomplete or missing capital markets, farm households tend to make production and investment decisions based on the assets they hold. Consequently, poorer households with fewer assets have more limited capacity to cope with climate-induced shocks, which may further affect their ability to recover from stresses by adopting farm technology that enhances agricultural productivity without additional investments (e.g., small-scale irrigation) for buffering the effects of shocks. This implies that resource-poor households are more likely to face chronic poverty and vulnerability.

6. CONCLUSIONS

Although the linkage between agricultural productivity and consumption has been the subject of long-standing interest in the literature, less is known in the context of sub-Saharan Africa about the distributional effects on consumption inequality of climate-induced shocks and associated variability in agricultural productivity. Using nationally representative panel data from Nigeria and Uganda, we examined the effects of variability in agricultural productivity on household consumption and consumption inequality using exogenous rainfall shocks as instruments. In investigating these relationships, we addressed several important policy issues. First, we examined the impact of climatic shocks on agricultural productivity to estimate the exogenous variability that affects consumption. Second, we assessed the impact of these climate-induced variability in agricultural productivity shocks on household consumption. Third, we investigated the effect of variability in agricultural productivity and other specific policy-relevant factors on consumption inequality at a given point in time. Finally, we exploited the panel nature of the dataset to examine the impact of climate-induced agricultural productivity shocks on intertemporal inequality over time.

To do so, we first studied the impact of rainfall shocks on variability in agricultural productivity using an FE model. We find that a negative rainfall shock decreases agricultural productivity by 7 and 36 percent in Nigeria and Uganda, respectively. Second, we then assessed the impact of variability in agricultural productivity on household consumption using the FE-IV model to account for the possible endogeneity of agricultural productivity. Controlling for other factors, a 10 percent increase in the level of variability in agricultural productivity decreases household consumption in Nigeria by 38 percent on average. For Uganda, a 10 percent increase in the level of climate-induced agricultural productivity shock decreases household consumption by 52 percent on average. Third, we applied both a conventional decomposition and a regression-based inequality decomposition approach to investigate the effect of variability in agricultural productivity on per capita consumption inequality during each of the survey years. In Nigeria, controlling for other factors, variability in agricultural productivity contributed an estimated 43, 20, and 33 percent to consumption inequality in 2010, 2012, and 2015, respectively. In the case of Uganda, variability in agricultural productivity contributed an estimated 25, 16, and 32 percent of consumption inequality in 2009, 2010, and 2011, respectively. Finally, we examined the effect of variability in agricultural productivity on changes in consumption inequality over time by comparing different periods in the panel data. We found that growing variability in agricultural productivity contributed to increased consumption inequality over time in both countries.

These results offer some useful insights for agricultural transformation and managing climate-induced shocks in Uganda and Nigeria, which are likely also to be relevant to other countries in the region. In the absence of water storage and irrigation systems to buffer the effect of climatic shocks, poorer smallholder farmers in particular bear high costs from climate-induced shocks both in terms of increased variability of agricultural productivity and declining per capita consumption. At the same time, this group of farmers has limited risk-bearing capacity and are highly vulnerable to these risks. Thus, rainfall shocks increase consumption inequality through their heterogenous effect on agricultural productivity, which is likely to reduce the ability of poorer households to overcome poverty (Barrett & Carter 2013; Dercon & Christiaensen 2011; Evangelista et al. 2013). Climatic shocks therefore undermine the ability of smallholder farmers to benefit from agricultural productivity changes. Considering the current pattern of technological change in sub-Saharan Africa, without complementary investments to reduce the effect of climate shocks, variability in agricultural productivity is likely to increase and levels of consumption inequality in rural areas will increase correspondingly. In addition to essential investments in farmer-managed small-scale irrigation systems, policies aimed at building resilience to climate risk – including targeted subsidies for risk-reducing inputs (e.g. drought-tolerant improved seeds), microinsurance, improved soil and water management, and agricultural knowledge and information systems accompanied by social safety nets – could help reduce household vulnerability and rural income inequality in the region.

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