Agricultural Productivity Growth in Africa: New Evidence from Microdata

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Abstract

Drawing on a newly harmonized longitudinal dataset covering more than 30,000 smallholder farms in six African countries, we analyze changes in crop productivity over a period ranging from 2008 to 2019. Because smallholder farmers represent a significant fraction of the world's poorest people, agricultural productivity in this context matters for poverty reduction and for the broader achievement of the Sustainable Development Goals. Our analysis measures productivity trends for nationally representative samples of farmers, using detailed data on agricultural inputs and outputs. In spite of substantial investments in African agricultural research, on the order of $2 billion annually in recent years, we find no evidence that smallholder crop productivity improved over this twelve-year period; indeed, the evidence suggests declining productivity in some countries. The results suggest that major challenges remain for agricultural development in Sub-Saharan Africa.

1. Introduction

Nearly two-thirds of the world's poor people live in sub-Saharan Africa, and more than 80 percent of Africa's poor lived in rural areas in 2018 (World Bank, 2020). Smallholder agriculture represents the main economic activity for this population. For this reason, the productivity of African smallholders has long been a concern for global development policy (Suri and Udry, 2022). In 2003, African heads of state committed themselves to increased investment in agricultural productivity and rural development, with that commitment enshrined in the Maputo Declaration on Agriculture and Food Security in Africa. Their commitment was echoed in the 2005 report of the UN Millennium Project, which called for a "doubling or more of agricultural productivity" in Africa as a key to reducing hunger and poverty. This target persists in the Sustainable Development Goals of 2015; both SDG1 and SDG2 link to agricultural productivity, and SDG Target 2.3 explicitly challenges the global community to "[b]y 2030, double the agricultural productivity and incomes of small-scale food producers."

Partly in response to these public commitments, spending on agricultural research rose steadily in the early 2000s. Public sector research spending averaged over $2 billion annually (measured in Purchasing Power Parity terms) across sub-Saharan Africa in the first fifteen years of the new millennium. Within that total, spending from the CGIAR, a consortium of international agricultural research institutions, reached over $500 million during this period (Beintema and Stads, 2017).

What do we know about the effectiveness of efforts to boost the productivity of smallholder agriculture in Africa? This paper reports on the most comprehensive effort to date to examine trends in smallholder productivity.

Our results draw on nationally representative panel surveys conducted as part of the Living Standards Measurement Study – Integrated Surveys on Agriculture (LSMS-ISA) in six African countries Ethiopia, Malawi, Mali, Niger, Nigeria, and Tanzania, and covering a period from 2008 to 2019. The data report changes in productivity experienced on over 130,000 plot observations from approximately 30,000 different households. For each plot, we observe detailed data on agricultural inputs and outputs.

We explore the characteristics and conditions of smallholder agriculture in Sub-Saharan Africa and investigate the correlates of agricultural productivity. We estimate productivity growth by regressing output changes on a rich vector of agricultural inputs, farmer and plot characteristics, and detailed data on local weather. We also explore heterogeneity in productivity growth between different farmers and plot types.

The main finding of the analysis is that there has been no significant improvement in smallholder crop productivity for our overall sample – although we find some heterogeneity at the country level, with some instances of growth. We analyze a number of alternative statistical models in which the overall productivity trend is negative and significant. Under some specifications, the overall trend is around zero. We observe greater productivity declines on plots managed by man than on those managed by women. In none of our models do we find a positive and significant overall trend.

Our findings raise concerns for the overall progress of agricultural development in Sub-Saharan Africa. They contribute to a literature (Alene, 2010; Block, 2014, 1995; Dias Avila and Evenson, 2010; Evenson and Fuglie, 2010; Fuglie, 2015, 2018; Fuglie et al., 2019; Fulginiti et al., 2004;

Gollin et al., 2021; Headey et al., 2010; Ludena et al., 2007; Lusigi and Thirtle, 1997) that has previously relied on aggregate national statistics, which have tended to show modest improvements in Total Factor Productivity (TFP). The two sets of findings are not necessarily inconsistent, so we do not argue that the new results overturn previous research. Some of our country-level results, for instance, align reasonably well with the widely cited data in the US Department of Agriculture's ERS International Agricultural Productivity (USDA, 2021). However, the quality of the national statistics has previously been questioned, and there are reasons to doubt the accuracy of the data for many countries (Calderón, 2021; Devarajan, 2013; Jerven and Johnston, 2015; Young, 2013). While many of these issues have been addressed by increasingly sophisticated econometric approaches that account for potential inconsistencies or changes to reporting quality, the underlying assumption is still that the data itself is accurate and reliable enough for inference.

Our analysis complements previous work by drawing on high-quality micro data and by using methods that allow us to control more fully for weather and input use. These data allow for a higher degree of control over the construction of output, input, and control variables, with the added benefit uniformity across surveys.

The remainder of the paper is structured as follows: Section 1 presents the detail of the survey data, the construction of harmonized variables, and the integration of detailed weather information. Section 2 details the estimation methods used for this analysis. Section 3 presents our findings, section 4 discusses these findings and their implications and concludes this article.

1 Data and variables

1.1 Survey data

This analysis uses harmonized plot-level data from the Living Standards Measurement Study – Integrated Surveys on Agriculture (LSMS-ISA). The LSMS-ISA surveys are considered the highest-quality micro-data sets for productivity analysis available for Sub-Saharan Africa. We harmonize data from six countries: Ethiopia, Malawi, Mali, Niger, Nigeria, and Tanzania.[1] The data covers a period from 2008 to 2019 with two to five survey rounds per country, resulting in over 130,000 plot observations from approximately 30,000 different households. We retain only households engaged in agriculture, dropping all non-agricultural households. The data cover agricultural inputs, output, and production practices at the level of individual plots for a specified agricultural season[2]; the agricultural variables link to a rich set of household, individual, community, and geographic variables. The surveys are based on nationally representative samples of population, which implies that they provide accurate representation of the smallholder sector, although they will miss the largest farms and those organized as commercial enterprises.

[1] Some LSMS-ISA country-surveys were excluded because they did not contain a minimum set of control variables for the analysis.

[2] The exact dates of an agricultural season is defined according to data from the Famine Early Warning System (FEWS) network. It refers to the period during which crops are reported to be planted, grown and harvested.

The surveys are longitudinal, such that communities, households (including split off households[3] in some countries), individuals, and parcels[4] can often be tracked across survey rounds: Households and individuals can be tracked across waves in five out of six countries (Tanzania, Ethiopia, Malawi, Niger and Nigeria). Plots or parcels can be tracked in Malawi, Ethiopia and Tanzania. In Mali, tracking is only possible at the level of the community (the enumeration area). Each country was observed in at least two surveys waves, and each country-wave is associated with a country-specific agricultural production season (**Table A. 1**). A country level description of the surveys can be found in Appendix 1.

The surveys use a stratified two-stage sampling procedure, with census enumeration areas (EAs)[5] as primary sampling units and households as secondary sampling units. The surveys are representative at the national and sub-national level and are stratified by administrative division and urban/rural levels. Survey estimates need to be weighted to be representative of the population at large. Each household in the dataset is assigned a sampling weight in line with the population it represents. In this analysis, sampling weights are adjusted to account for households with multiple plots and the exclusion of non-agricultural households (see Appendix 2).

The principal outcome variable of interest for our analysis is yield (output value per hectare of land). Plots in our sample frequently grow multiple crops on the same plot and we therefore aggregate crop production at the plot level using a set of crop prices as weights. Specifically, for each seasonal crop[6], output quantities are obtained, using conversion factors for non-standard units where applicable, valued at constant prices for each country, and then converted to 2020 USD (Appendix 4). By using constant prices, we avoid the possibility that year-to-year changes in the relative prices of crops could create fluctuations in yield value, which in turn could affect the estimated productivity trend. We replicate the analysis using wave- and region-specific current prices (results can be found section 4). We retain only plots on which seasonal crops are grown. We dropped plots whose harvest could not be valued, plots on which harvest was missing, and plots entirely dedicated to perennial crops.[7] We show the sensitivity of our findings to missing values in section 4.3.

[3] Split-off households are households composed, partly or entirely, of members from a household in a previous wave, that have moved out and constituted a new household.

[4] Parcels are defined as “any piece of land of one land tenure type entirely surrounded by other land, water, road, forest or other features not forming part of an (agricultural) holding or forming part of the (agricultural) holding under a different land tenure type” (*World Programme for the Census of Agriculture 2020*, n.d.).

[5] Enumeration areas are geographical units defined for census purposes (*World Programme for the Census of Agriculture 2020*, n.d.)

[6] Seasonal crops are those that are planted and grown within the timeframe of the agricultural season. This excludes permanent (or perennial) crops, which have a growing cycle that is longer than a year.

[7] Plots may record missing harvest values for a number of reasons, including delayed harvest seasons, unit non-response, missing conversion factors for non-standard quantity units, or inability to value crops due to the absence of recorded sales across the whole dataset. There were also rare cases of absent plot size measurement, which prevented the calculation of yield values. When a certain crop on a plot could not be valued, but one or more other crops contained valid output values, plot-level output was still calculated, and a dummy variable was included to flag the fact that a portion of the plot-level yield value is missing.

The agricultural input variables in our analysis are land area in hectares, family and exchange labor (i.e. labor exchanged with other households in the community) in labor-days, as well as the cost of hired labor, of seed inputs, and of inorganic fertilizers[8], valued at constant USD prices. All input variables are expressed in effective, per-hectare terms for each plot.

Input and output variables were winsorized at the 99th percentile. Seed and output values, as well as total labor days, were additionally winsorized at the 1st percentile (while preserving output values of 0, to account for full losses). Land areas were not winsorized as they are mostly measured via GPS, but extreme plot sizes that are above 100ha are dropped from the sample.

In addition, an agricultural assets index was computed using a principal component analysis (PCA), quantifying agricultural asset ownership in a single dimension drawn from an inventory of household assets.

We also create a rich set of control variables capturing plot, farmer, and household characteristics: plot-level dummy variables for the use of pesticides, the use of organic fertilizers (e.g. compost, manure), if intercropped, if irrigated, whether the plot is owned by the household, and the occurrence of crop losses due to shocks during the agricultural season (e.g. drought, flood, fire); age, gender, and formal education status of the plot manager; household size, household shocks (e.g. death of a family member), as well as livestock ownership, household electricity access, urban/rural status.

For the main statistical specification, we harmonized the data and created these variables at the plot-level. For alternative specifications, we aggregate the dataset to the household/farm level and to the plot manager/farmer level. For this, outputs and inputs are summed for each household or plot manager, maximum values of indicator variables were retained.[9] Another version of the dataset was aggregated at the cluster level. In that case, the mean of household indicator variables was computed (e.g. the percentage of households in the cluster with irrigated plots).

The outcome, input, and control variables suffer from varying degrees of item non-response. Overall, the share of missing values in input, and control variables included in the main specification range from zero to 8.77 percent (see Table A. 2). Given the high dimensionality of the main statistical specification we use, a sample reduction of around 17% is observed as the model parameters are estimated, representing a reduction of approximately 8% in the number of households in the dataset. A number of these missing values resulted from unavailable conversion factors for non-standard fertilizer or seed weight units, as well as missing sale/purchase information for certain classes of labor, seeds, or fertilizers, which could therefore not be valued. Absent responses to certain questions and/or sections within surveys were a further source of missing values.

[8] Inorganic fertilizers (or mineral fertilizers) are substances that are manufactured through an industrial process, applied to "supply plants with nutrients or to enhance plant growth" (*World Programme for the Census of Agriculture 2020*, n.d.). UREA, NPK and DAP are examples of inorganic fertilizers

[9] In this case, the interpretation of indicator variables changes slightly. For example, the indicator that a plot is owned is converted into an indicator that at least one plot is owned by a given household or plot manager, depending on the level of aggregation.

1.2 Climatological and other geospatial data

To account for the impact of weather variation on agricultural productivity growth, we incorporate detailed weather data into the survey data. Households in the LSMS-ISA surveys are georeferenced via GPS (see Appendix 4), which enables merging the survey data with spatially explicit weather data. These recorded geolocations are slightly offset from the true locations, in order to preserve the anonymity of households and survey villages, so our weather data are adjusted accordingly to account for the offset. However, given the coarseness of the weather data, it is unlikely that the coordinate obfuscation significantly impacts the effect of weather controls (Michler et al., 2021).

Daily and monthly temperature and precipitation series were obtained by combining observational (weather station and satellite) and reanalysis (model-based) climate data products. Temperature data were drawn directly from ERA5, a large climate reanalysis produced by the European Centre for Medium-Range Weather Forecasts (ECMWF), available on regular latitude-longitude grids at a 0.25° resolution, or about 25km close to the equator. Precipitation data were drawn from Climate Hazards Group InfraRed Precipitation with Station (CHIRPS) database, a dataset that combines observations from real-time meteorological stations with infra-red data. These data are available at a 0.05° resolution, corresponding to approximately 5km around the equator.

These were incorporated into the survey data based on household GPS coordinates (clusters) and the timing of the agricultural seasons[10] covered in our data. Linear interpolation was used to downscale these weather data as they were matched to clusters in the survey data.

For each cluster, a large set of variables based was created based on the raw temperature and precipitation series, in line with recent literature (Karl et al., 1999; Mérel and Gammans, 2021; Michler et al., 2021). These are listed in Table A. 2.

We further make use of some of the geospatial variables which are disseminated with the LSMS-ISA survey datasets (see National Bureau of Statistics, 2021a). Specifically, agro-ecological zones (provided by IFPRI, using WorldClim climate data), distance to the nearest town, distance to the nearest major road (both log-transformed, in km) and elevation (log-transformed, in m). The latter three variables are drawn from SRTM 90m and provided by NASA. In addition, a soil quality index was computed, based on remote-sensed nutrient availability, nutrient retention capacity, rooting conditions, oxygen availability to roots, excess salt, toxicity and workability data drawn from the Harmonized World Soil Database, provided by the FAO (Central Statistical Agency and Living Standards Measurement Study (LSMS), World Bank, 2021; Ministry of Finance and National Institute of Statistics, 2016; Ministry of Rural Development, 2019; National Bureau of Statistics, 2021a, 2021b; National Statistical Office, 2020).

2 Estimation Methods

We begin with a set of summary statistics for outcome, input, and control variables, presenting weighted averages, medians, and standard errors. We then explore the relationship of some key

[10] Information from FEWS-NET was used to determine the length and timing of each season.

independent variables with the outcome variable (i.e. yield values; see Appendix 3 on valuation methods), in a weighted regression with country fixed effects.

For the core part of the analysis, we estimate productivity growth over time. For this, we first consider the raw time trend of yield (output per unit of land) in our dataset using an Ordinary Least Squares (OLS) regression of yields on the time trend variable, with country fixed effects (Model 1).

$$\ln\left(\frac{Y_{it}}{L_{it}}\right) = \alpha + \beta year_t + C_i + \varepsilon_{it} \tag{1}$$

where Y refers to the value of output in constant USD, L to plot area in hectares, and α denotes a constant. C_i captures country fixed effects and ε_{it} is a residual. The model, like all following specifications, is implemented with population weights which reflect the multi-stage sampling design of each country and wave. Standard errors are clustered at the EA-level to account for correlations in outcomes between nearby plots in the same community.

Yield is a relatively simple measure of productivity. TFP is a more complete measure of productivity that effectively accounts for changes in an index of all inputs. There are numerous methodological challenges in accurately measuring TFP, due to the potential for reverse causality and other endogeneity of inputs. In our analysis, we approximate TFP with a simple approach in which the input weights are derived from regressing output per unit of land on our large set of explanatory variables. Specifically, we implement a cross-country plot-level regression of yield on effective inputs, a linear time trend, a set of weather variables and a set of control variables, including crop mix and country fixed effects (Model 2, our preferred specification). This specification for plot i in agricultural season t, can be written as:

$$\ln\left(\frac{Y_{it}}{L_{it}}\right) = \alpha + \beta year_t + \sum_{j=1}^{J} \gamma_j \ln\left(\frac{I_{jit}}{L_{it}}\right) + \sum_{l=1}^{K} \delta_l \left(X_{lit}\right) + f(W_{it}) + \theta M_{it} + C_i + \varepsilon_{it} \tag{2}$$

where I is a vector of input variables indexed by j (where $j = 1, \dots, J$), and X a vector of household and plot controls indexed by l (where $l = 1, \dots, K$). The agricultural assets index and log-transformed plot area variables was not scaled by plot area and are therefore included in vector X according to this syntax. The function $f(W_{it})$ represents a set of weather variables. The term M_{it} denotes main crop effects[11]. The coefficient of interest, β is the coefficient for continuous time trend, where $year$ is defined as the year of the end of agricultural season. Finally, ε_{it} denotes a residual.

[11] In this paper, main crops are defined as crops which have the highest production value on the plot in a given agricultural season. Main crops were then grouped into ten categories: barley, beans/peas/lentils/peanuts, maize, millet, nuts, rice, sorghum, tuber/root crops, wheat and an "other" category.

The weather and geospatial controls included in our preferred specification are selected using a Least Absolute Shrinkage and Selection Operator (LASSO) formula. Only a subset of predictors was included in $f(W_{ht})$ to account for the impact of weather while maintaining a degree of sparsity. Furthermore, weather metrics can impact productivity in different ways across settings (Michler et al., 2021), and it was therefore important to adapt the selection of weather and geospatial variables to different samples considered (eg. in within-country regressions). The LASSO method reaches these goals by regularizing coefficients, which entails imposing a constraint within the OLS optimization problem (Hastie et al., 2015). A plugin iterative formula is used to select this constraint parameter (Belloni and Chernozhukov, 2011).

In addition to models 1 and 2, we implement several alternative statistical models to measure overall productivity trends. First, we aggregate input and output variables to estimate a farm-level (rather than plot-level) productivity trend (Model 3). Second, household-, farmer- and cluster-level fixed effect models were estimated (Model 4, Model 5, and Model 6). Mali is excluded from the analysis for models 4 and 5, as households and farmers cannot be tracked. Finally, we re-value inputs and outputs using time- and region-specific current prices, rather than constant prices (Model 7). We run the regressions both on the full cross-country sample and for each country separately.

3 Results

In this section, we present the results of the analysis. We begin with a simple descriptive exploration of key variables of interest and characterize their relationship with productivity. We then present the main results on productivity growth. We examine differential productivity growth patterns across the sample and assess concurrent trends in inputs and control variables.

3.1 Yields, inputs, farmer characteristics, and farming conditions

Basic summary statistics of the outcome variable (yield values), inputs and control variables are presented separately for each country-wave in Table A. 3 and Table A. 4 in the Appendix (Figure A. 1). While plots in our sample are generally small, with two out of three plot observations below 0.5 hectares, there is substantial cross-country heterogeneity. In the two West-African Sahel countries Mali and Niger plots are much larger than in the other countries, on average larger than 2 hectares.

There are also substantial differences in yields across countries, with Nigeria standing out for higher average yield levels (Figure A. 1). Across the study countries, plots are cultivated with a diversity of crop types and mixes and at different levels of crop diversification (Figure 1).

We show the distribution of plots across countries into different Meybeck relief classes (Meybeck et al., 2001; Figure 1). There is a large variety of terrains, from high mountains in Ethiopia to plains in Nigeria and Tanzania[12].

[12] We could not gather this information in Mali

We find that yields vary substantially across different crops cultivated. Barley, rice, and nuts have between 25% and 50% higher yields than maize, while wheat and tubers and root crop yields are around 75% and 100% higher (Figure 2). These results are based on a regression specification which includes country fixed effects, so these patterns are driven by yield differences across countries.

Figure 1. Percent of plots by main crop category and Maybeck relief classes for each country

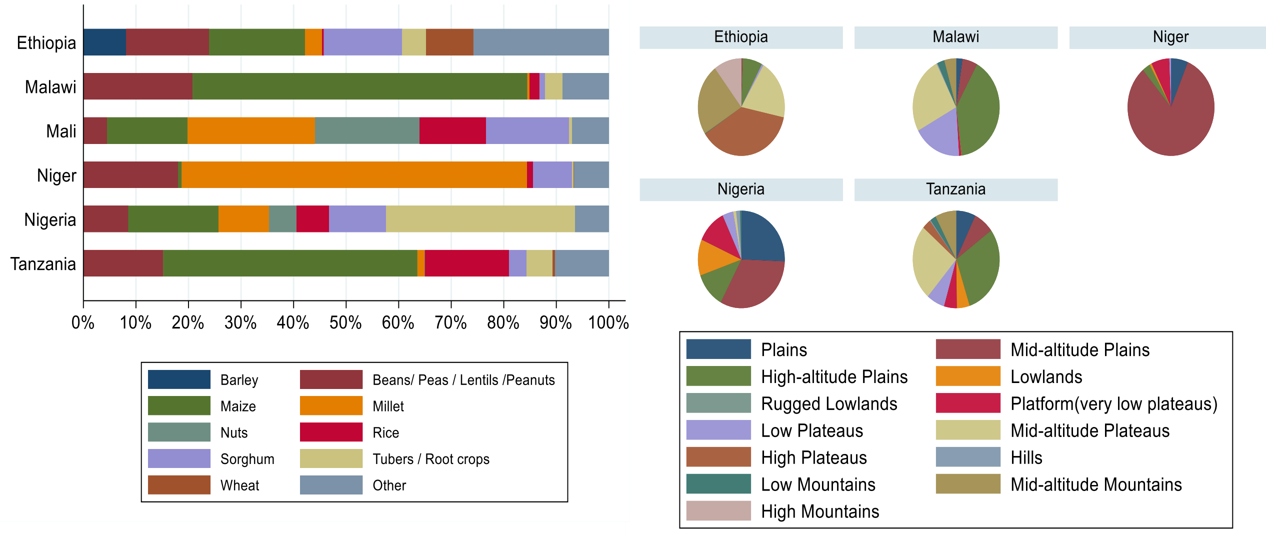
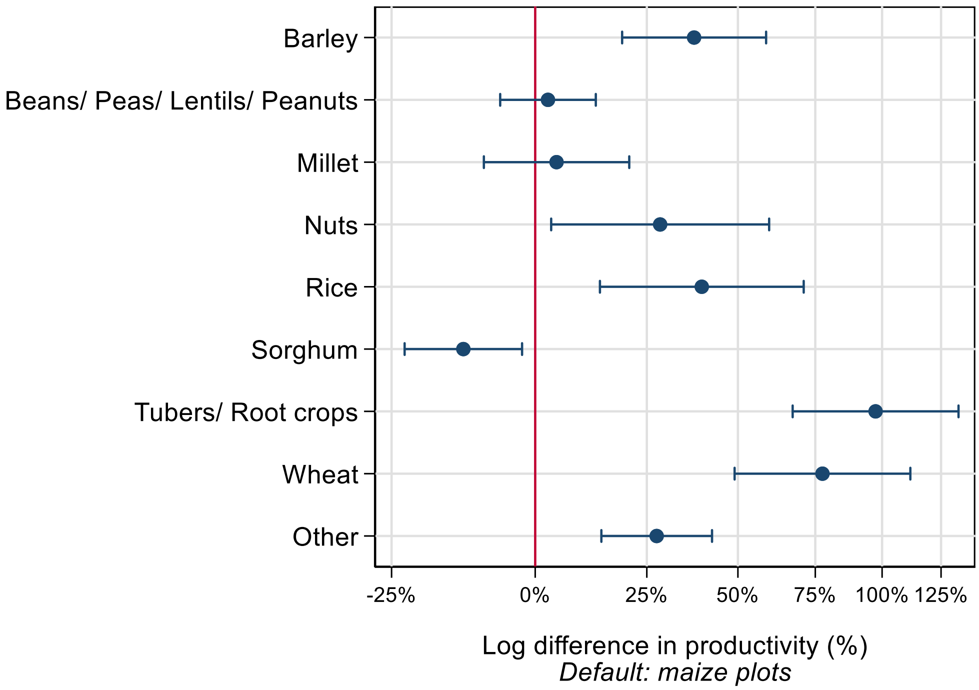


Figure 2. Average yield value by main crop category



Note: all coefficients plotted above are obtained from a regression of log yields against main crops, with country fixed effects.

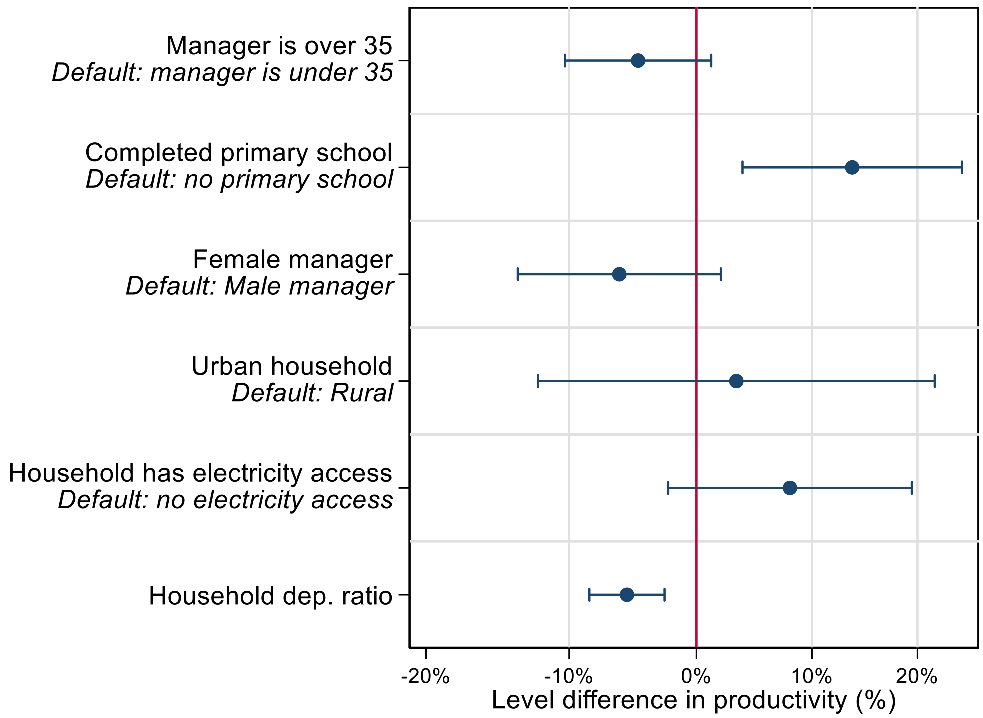
We further assess key farmer and household characteristics. Specifically, farmer gender, age, and education, as well as whether the farm is urban and electricity access and household dependency ratio, the latter two to proxy farmers' welfare levels.

Across our study countries, a minority of farmers are women. Across countries, women manage approximately 20% of plots. However, the share of plots managed by women varies between countries. A higher percentage of plots is managed by women in Malawi than in Niger and Mali (Table A. 5). Women also manage smaller plots, on average, than men (Figure A. 4).

Close to 77% of plots across countries are managed by farmers 35 years of age and over. Malawi and Niger have the relatively highest share of younger farmers (under 35) at 36% and 34%, respectively, with the lowest share of young farmers in Nigeria at 17%. At the same time, most plots are managed by farmers who have no primary education. This is true for more than 9 in 10 plots in Ethiopia, Mali, Niger, and Tanzania. In contrast in Nigeria, almost half of farmers have at least primary education, compared to about 30 percent in Malawi. 30 percent of plots are managed by households with access to electricity and around 10 percent of plots are in urban areas (Table A. 5).

How do these characteristics relate to productivity? Overall, yield levels differ less by farmer and household characteristics than by crop types (Figure 3). After controlling for country differences, only farmer education and the household dependency ratio is significantly associated with yield values. Plots managed by farmers with primary education have around 13% higher yield values, and a unit increase in the household dependency ratio is associated with a 6% decline in yields. Nominally, plots managed by women and older managers have slightly lower yields (-6% and -5%, respectively) and plots managed by households with electricity access and in urban areas have slightly higher yields (+7% and +3%, respectively) – however, none of these coefficients are significantly different from zero after controlling for country fixed effects (Figure 3).

Figure 3. Correlations between average yields and farmer/household characteristics



Note: This graph plots the coefficients and 95% confidence intervals for a set of coefficients resulting from univariate regressions of log yields against various controls. Most coefficients are estimated differences of yield values for a category of plots compared to a baseline (default) category. Results from the household dependency ratio *variable are interpreted as the average % change in yields for a 1 percentage point increase in the household dependency ratio. Country fixed effects are added to all specifications. The unit of the x-axis has been transformed to account for the log-linear nature of the specification.*

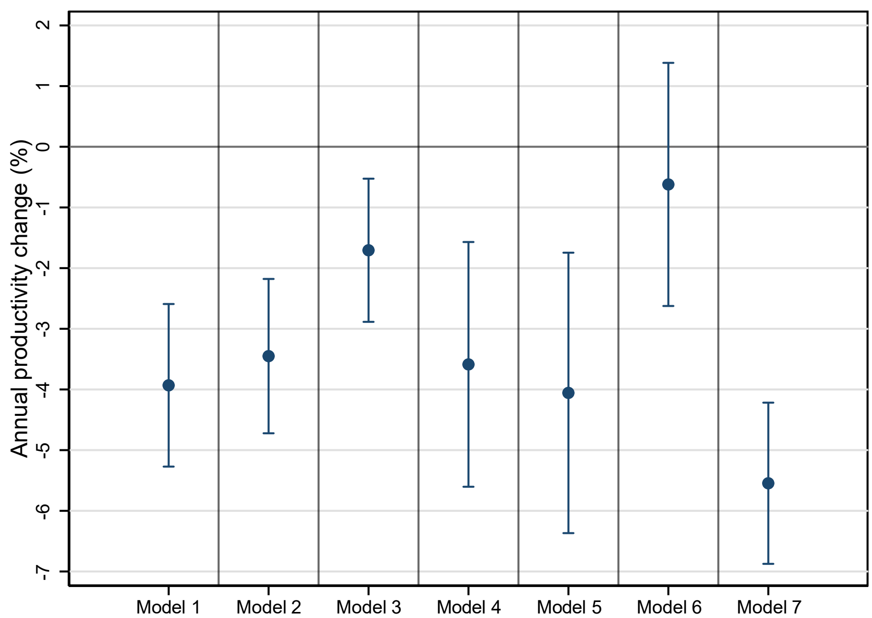
Weather and climate are understood to be important determinants of agricultural outcomes, especially in rainfed smallholder agriculture. The relationship between yields and weather variables is explored in, which present a series of scatterplots between yield and various weather controls. In addition, we model the relationship between yield and each weather variable as a fractional polynomial, in order to reflect the much-documented non-linear nature of weather impacts on crop outcomes (e.g. Hsiang, 2016; Mérel and Gammans, 2021). These graphs exhibit a dome-shaped relationship between yields and measures of temperature maximum, range and standard deviation, as well as daily and 5-day consecutive precipitation maximums, length of longest wet spells, and a precipitation intensity index (calculated as a ratio of precipitation amounts over the number of wet days). Furthermore, there is a negative relationship between yields and the maximum length of dry spells. In addition, farmer-reported losses due to crop shocks such as droughts or floods are common on the plots in our sample (Figure A. 5).

3.2 Productivity trends in African agriculture

In this section, we summarize the results of the analysis of productivity growth over time in the full cross-country sample of plots and separately for each country. We use seven regression models (see Appendix 5), with the first a simple model of the raw time trend in yields and the second our preferred specification for measurement TFP growth.

We find no evidence of growth in productivity in the full cross-country sample of agricultural plots between 2008 and 2019. In fact, a negative time trend is found across most of our statistical specifications (Figure 4). The raw time trend of crop yield in our sample is -3.9%, with the 95% confidence interval (CI) ranging from -5.3% to -2.6% (Model 1). Next, estimating TFP in the plot-level model using a full set of plot-level controls (Model 2), we find an annual productivity decrease of -3.5% (95% CI: -4.7% to -2.2%).

Figure 4. Estimated coefficients of productivity change across different regression models



*Note: This figure plots coefficients and 95% confidence intervals of productivity change estimates from various regression models. **Model 1** is a simple regression of yield on a linear time trend and country dummies. **Model 2** is a plot-level model, controlling for inputs, weather, country dummies, and other control variables. **Model 3** is analogous Model 2 but using data aggregated at the household level. **Model 4** is a household fixed effects model. **Model 5** is a plot-manager fixed effects model. **Model 6** is a cluster fixed effects model. **Model 7** is analogous to Model 2 but using current, instead of constant, prices. See Table 5 for point estimates and a full list of variables.*

We estimate a farm-level (rather than plot-level) productivity time trend of -1.7% per year (Model 3; 95% CI: -2.9% to -0.5%). The household, farmer and cluster fixed effects models find productivity changes of -3.6% (Model 4; 95% CI: -5.5% to -1%), -4.1% (Model 5; 95% CI: -6.4% to -1.7%) and -0.7% (Model 6; 95% CI: -2.6% to 1.3%), respectively. Finally, when using time- and region-specific current prices, rather than constant prices, to value yields and inputs, we estimate a productivity decline of approximately -5.6% per year (Model 7; 95% CI: -6.9% to -4.2%). The results are qualitatively robust to several additional robustness checks, which we discuss in section 5.

3.2.1 Differential productivity trends across countries

There is substantial cross-country heterogeneity in productivity trends over time. We find significant declines in raw yields (Model 1) in Malawi and Nigeria, no significant changes in Ethiopia, Mali, and Tanzania, and positive growth in Niger (Table 1).

We also run the preferred model (Model 2) with a full set of plot-level controls to estimate TFP for each country separately. We find robustly negative changes in productivity in Nigeria (-4.8%:, CI -6.9% to -2.7%) and Malawi (-3.5%; CI: -5.1% to -2%) and no significant changes in Tanzania (-0.3%; CI: -2.7% to 2%), Ethiopia (0.0%; CI: -2.6% to 2.6%) and Mali (-1.7%; CI: -6.7% to 3.2%). There is an apparent growth spurt, however, in Niger (28.5%; CI between 24.7% to 35.9%), though we only observe the country at two points in time. The results from Nigeria have the most significant effect on the aggregate time trend. Removing Nigeria from the sample would lead to a time trend indistinguishable from zero in the preferred model (see Section 4.3). The cases of Ethiopia, Tanzania, and Mali have relatively large standard errors, such that some productivity growth is consistent with our findings.

Table 1. Country level results

		Ethiopia (1)	Malawi (2)	Mali (3)	Niger (4)	Nigeria (5)	Tanzania (6)
Model 1: Simple time trend	Annual time trend	0.00198 (0.0138)	-0.0378*** (0.00710)	0.00743 (0.0225)	0.353*** (0.0260)	-0.0862*** (0.0108)	0.00176 (0.0138)
	Sample size	36,195	17,056	30,817	8,184	17,148	7,383
	R-squared	0.000	0.010	0.000	0.120	0.020	0.000
Model 2: Preferred plot-level model	Annual time trend	-0.00005 (0.0131)	-0.0354*** (0.00783)	-0.0174 (0.0251)	0.303*** (0.0284)	-0.0483*** (0.0108)	-0.00371 (0.0120)
	Sample size	36,195	17,056	30,817	8,184	17,148	7,383
	R-squared	0.237	0.336	0.469	0.446	0.408	0.379

Note: This table presents regression results (point estimates and standard errors in parentheses) for a set of country-level models. ***Model 1*** *is a simple regression of yield on a linear time trend.* ***Model 2*** *is a plot-level model, controlling for inputs, weather, country dummies, and other control variables to estimate TFP. All regressions are weighted. Dependent variable output in constant USD per hectare.*

3.2.2 Farmer characteristics and agricultural productivity trends

We examine the possibility of differential productivity trends across plots managed by women and men. We saw that fewer plots are managed by women, that those are smaller, and slightly less productive in terms of yield levels (section 4.2.1). To assess differential productivity changes over time, we make use of the preferred TFP specification and add an interaction between the time trend and the female plot manage dummy variable, and further add run separate specifications for plots run the by women and men. In the interaction specification, the coefficient on the time trend variable captures productivity changes for plots managed by men. The interaction captures the difference in productivity changes on plots managed by women relative to plots managed by men. The productivity change of plots managed by women is the sum of the two.

Overall, we find that the time trends differ significantly between plots managed by women and men. Plots managed by men exhibit a significant productivity decline of 4.27% in the preferred specification, while productivity on plots managed by women neither declined nor increased. (Table 2). This pattern holds true at the country-level in Tanzania, Niger and Nigeria. There is no significant difference in Ethiopia and Mali. In Malawi, the country with the highest proportion of female plot managers (Table A. 5), we find a contrary development. Plots managed by women saw steeper productivity declines than those managed by men.

Table 2. Differential productivity trends for plots managed by men vs women

	Baseline results (model 2)	**Annual time trend for male plot managers**	**Interaction term (annual time trend × gender dummy variable),** difference in the annual time trend plots managed by women relative to men	**Annual time trend for female plot managers**
	(1)	(2)	(3)	(4)
Pooled sample	-0.0345***	-0.0427***	0.0388***	-0.004
	(0.00649)	(0.00711)	(0.0100)	(0.0094)
Ethiopia	0.000	-0.00388	0.0236	0.0197
	(0.0131)	(0.0142)	(0.0196)	(0.0188)
Malawi	-0.0354***	-0.0278***	-0.0174**	-0.0452***
	(0.0078)	(0.00794)	(0.00780)	(0.0096)
Mali	-0.0174	-0.0226	0.0348	0.0122
	(0.0251)	(0.0262)	(0.0439)	(0.044)
Niger	0.303***	0.283***	0.139***	0.422***
	(0.0284)	(0.0291)	(0.0489)	(0.05145)
Nigeria	-0.0483***	-0.0542***	0.0361**	-0.0181
	(0.0108)	(0.0116)	(0.0177)	(0.0167)
Tanzania	-0.00371	-0.0144	0.0387**	0.0243
	(0.012)	(0.0137)	(0.0166)	(0.0148)

Note: This table plots coefficients of various dependent variables in a modified version of model 2 (with an added interaction, the coefficient of which is reported in column (3)) across different samples. Column (4) plots the estimated effect of the interaction combined with the time trend.

We replicate this analysis for farmer education (plot manages has at least primary education) and age (plot manager is 35+). However, we do not find any significant differences along these dimensions (Table A. 10 and Table A. 11).

3.2.3 Differential productivity trends by yield level, plot size, and farm size

We assess the heterogeneity of productivity growth across more and less productive plots. For that, we calculate yield deciles by country-wave and pool country-level observations for each decile, obtaining ten separate cross-country data sets, each representing one yield decide. We run the preferred specification on the ten sub-samples separately and plot the ten coefficients in Figure A***. 7***. Productivity growth is negative for all deciles. That is especially the case in higher percentiles of yield value, although we note a large confidence interval larger for the first decile.

We also investigate the heterogeneity of productivity growth across farm size and plot size deciles, that is, between small and large plots and farms. Following the same approach as before, we find no clear patterns of heterogeneity.

3.2.4 Trends in inputs use, farming practices, farmer characteristics, and conditions

Here we explore changes in inputs, farmer characteristics, farming practices, and conditions over time, which may help interpret the headline result of slumping productivity as well as some of the country developments. For example, growing input intensity in production may be reflected in (temporarily) lower productivity levels if output increases less than proportionally with input intensification. Similarly, an increasing incidence of crop shocks could depress productivity over time.

We estimate the raw time trend in input variables, by regressing each variable of interest on a linear time trend and country fixed effects, analogous to Model 1 above. We replicate the analysis using a second regression model with a fuller set of controls similar to Model 2 above. The results are shown in Table A. 12, Table A. 13, Table A. 14 and Table A. 15.

The evidence on input intensification is mixed, as time trends in inputs are somewhat divergent across inputs and countries. In the full cross-country sample, there is no significant change in plot size but a small reduction in family labor (-1.6% per year), arguably the two most important inputs. There is no significant trend in inorganic fertilizer value and a decline in the value of seed inputs (-3.7%). Underlying these relatively small overall changes are once again more pronounced country-level changes, both positive and negative. Notably, however, there is significant growth in the value of hired labor input of 14.3% percent per year in the full sample. At the country level, hired labor value increases in Ethiopia, Mali, Niger, and Nigeria, stays constant in Tanzania, and declines in Malawi. We replicate this analysis on the summed input values for hired labor, seeds, and fertilizer, finding an increase of 5.6% per year in this aggregate input variable. While this suggests some measure of overall input intensification, it does not account for household labor and plot area, which, if anything, have been contracting. However, we do find some evidence of production expanding at the extensive margin: total farm area (rather than plot area) is increasing at a rate of around 4% per year in our data, driven by an increase in the number of plots cultivated per farm (Table A. 12. **Time trend in input variables** .

Declining agricultural productivity could also be a result of declining input quality that is not captured by our control variables. In Table A. 16, we examine the evolution of a set of soil quality measures available in our dataset (see Section 2.2). Our data do not record a measurable change in the incidence of soil quality issues, although there may exist a combination of these variables under which changes in soil quality could be detected.

Next, we explore changes in production patterns, specifically crop diversification and the incidence of raising livestock along crop farming. Farmers may choose to diversify or change production patterns to reduce vulnerability to climate shocks or in reaction to changing prices, both of which could conceivably result in reduced productivity over time. We find no signs of crop diversification, but rather some limited evidence of concentration in the pooled sample (Table A. 14): The number of crops per plot and the prevalence of intercropping slightly decrease through time (-0.03 units and -1.69%, respectively). The incidence of growing perennial, in addition to season, crops also decreases marginally through time in the pooled sample. Finally, the incidence of livestock raising among the crop farmers in our sample decreases by around 1 percent per year. Underlying these aggregate trends, we find some country heterogeneity. Note that this analysis misses potential changes on crop varieties and focuses on changes on the extensive, rather than intensive, margin.

We assess changes through time in farmer characteristics. The probability of being a female plot manager, of a plot manager being over 35, and of a plot manager having primary school education are all increasing throughout the study. However, in all three cases, the coefficient on the time trend less than 1% in the pooled sample, unlikely to have large impacts on the productivity time trend.

Finally, we assess the trends in farming conditions. Overall, we find no increase in the incidence of crop losses due to environmental shocks. However, there are increases reported shock incidences in Ethiopia (+1.5%), Malawi (+1.9%), and Nigeria (+3.6%). In Niger, the only country with productivity growth, there was a 15% decrease in the incidence of shock-related crop losses. In all, crops shocks may offer a partial explanation for the productivity growth trends we observed.

3.3 Robustness checks

We run several additional specifications to assess the robustness of our results on slumping productivity growth. To examine the sensitivity of overall results to specific country patterns, we drop from the pooled sample the observation from one country at a time and run the preferred specification (Model 2) on the resulting sub-samples. Results are shown in Table A. 17. Two countries have a noticeable effect on the time-trend: Nigeria and Ethiopia. When dropping Nigeria from the pooled sample, the time trend in this specification becomes less negative (-0.1%) and is not statistically significantly different from zero. When dropping Ethiopia from the pooled sample, the coefficient becomes more negative at -4.3%. In analogous fashion, we drop each main crop type from the pooled sample to assess the potential heterogeneity of the trend in productivity across types of crops. The negative time trend is robust to the omission of the various crop types (Table A. 18).

Next, we vary the dependent variable to explore other measures of productivity than yield: (1) harvest value per labor-day on the plot, and (2) harvest value per dollar of seed value used on the plot, both expressed in constant USD. Using a version of the preferred specification, we find very similar productivity time trends as in the main results (Table A. 19).

We further assess the sensitivity of main results to alternative outlier correction methods. In the preferred specification, the upper end of the distribution of yield and main input variables was winsorized at the 99th percentile within each country-wave. We apply alternative outlier correction methods to the outcome variable, that is, winsorizing at the 95th percentile, trimming at the 99th and 95th percentiles, median replacement above the 99th and 95th percentiles. These alternative computations of the outcome variable do not qualitatively change our conclusions (Table A. 20). Trimming at the 95th percentile has the largest impact on annual the time trend coefficient, pushing it up to -0.6% and no longer statistically significant.

Given the incidence of item non-response in the sample (Table A. 2), another robustness check is to assess the influence of missing values on the results. To this end, missing observations were imputed with the same random number and an indicator variable is added in the regression, equal to one if the observation contains a missing value for each independent variable. In this way, results could be estimated on the full sample (Table A. 21). Following this strategy, we estimate a time trend of -3.6% relative to the baseline time trend of -3.45%. This test suggests that our conclusions are robust to the influence of missing values.

4 Discussion and conclusions

The results of our analysis raise numerous questions and concerns. The low (and potentially negative) rates of productivity growth offer discouraging indications in relation to Africa's progress towards targets that have been such as SDG Target 2.3. Insufficient productivity growth will pose challenges both for poverty reduction and for meeting the region's projected food needs. With impacts from climate change likely to increase sharply in the years ahead, these concerns loom even larger.

A particular concern is that there is little evidence for productivity benefits from the substantial investments that have been made in the agricultural sector over the past twenty years, including in agricultural research. Have investments been insufficient in scale – particularly in relation to the challenges of climate change and environmental degradation? Investments have been highly uneven across Africa (Fuglie et al., 2019), with many countries experiencing little or no growth in research expenditure or other sector-specific investments. Or is it perhaps too soon to see the benefits of these investments realized? Given the nature of agricultural research, for instance, it is not uncommon to see long time lags between research and impact.

Another point of interest is the comparison of our findings with macro estimates of TFP growth at the country level. Data from the US Department of Agriculture's ERS International Agricultural Productivity platform suggests slow TFP growth in many of our study countries (USDA, 2021), somewhat in keeping with our headline results. Underlying slow productivity growth, however, is a significant increase of total output and commensurate increase in total inputs. This pattern would suggest output growth at the extensive margin, without significant productivity gains, which has implications for land degradation, land use change, and ultimately food security. In this analysis, we find a significant increase in hired labor. We also find some evidence of greater total land use, as farms cultivate more plots. More research will be needed to analyze productivity declines reflect these increases in inputs.

The analysis itself faces limitations. Although the LSMS-ISA data have been extensively tested and validated, the surveys rely on farmer recall of yield and inputs, which have been shown to be imperfect (Arthi et al., 2018; Desiere and Jolliffe, 2018). However, these issues should be less problematic in our panel data than in cross-section analysis; for this to be driving the negative results in our estimates of productivity growth, it would need to be the case that farmer misreporting was changing over time in a systematically biased way.

Our data cover a relatively short time span, and for each country, we have relatively few waves of data. This reduces our statistical power but should not affect the point estimates for productivity growth. These are panel data, tracking farmers over time.

As noted above, our data come from surveys of smallholder farmers. Some researchers have argued that stagnation of productivity in the smallholder sector may be offset by the emergence of a productive larger-farm sector (Jayne et al., 2019). Our analysis does not allow us to judge this hypothesis directly, but we note that smallholder producers account for very large fractions of output in the countries that we study; for example, 98.6% of cereal production in Tanzania came from smallholder farms (Tanzania National Bureau of Statistics, 2021). If similar numbers pertain in other countries, it seems implausible that rising productivity on large farms could offset the trends that we observe in our sample.

We cannot rule out the possibility that changes in weather or climate may account for the observed changes, either directly or indirectly (e.g., through impact on the pest and disease ecology). Given the multidimensionality of weather data, it is possible that there exists some construction of a weather variable that might account for the observed decline in productivity. Our analysis shows that weather variables have a significant impact on productivity levels. We also observe some increases in farmer reported crop losses due to climate shocks in those countries where we observe significant productivity declines. However, the explanatory power is not sufficient to fully account for the changes that we observe over time.

Given the needs for improvements in productivity, it is tempting to close by calling for increased investments in agricultural productivity. But the lack of demonstrable positive impact calls for a careful examination of the factors holding back productivity growth. Agricultural investment strategies must recognize the huge challenges that smallholder agriculture in Africa face. Among these challenges are rapidly evolving disease and pest ecologies, soil degradation, and climate change.

This study also underscores the importance of long-term panel data that make it possible to monitor the evolution of productivity in smallholder systems and to measure the impact of agricultural investments.

Appendix

Appendix 1: LSMS- ISA survey description

In Ethiopia, data from the Ethiopian Social Survey (ESS) were assembled across four survey periods: 2010/2011, 2012/2013, 2014/2015 and 2017/2018. The panel was fully refreshed in wave 4, and households are therefore not tracked across more than three waves. Split-off households (see Section SI.I) were not tracked in Ethiopia. The first wave of the panel survey (ESS 2010/2011) is only designed to be representative of rural areas and small towns, and the sample was expanded to urban areas from wave 2 onwards (ESS 2012/2013). Furthermore, waves 1 to 3 of the sample were designed to be representative of the most populous regions of the country (Central Statistical Agency and Living Standards Measurement Study (LSMS), World Bank, 2021). The main Ethiopian agricultural season (the Meher season) ranges from April to January (inclusive), according to FEWS.

In Malawi, data from the Integrated Household Panel Survey (IHPS) were assembled across four periods: 2009/2010, 2012/2013, 2015/2016 and 2018/2019. All split-off households were tracked in Malawi. A random half of EAs were dropped from the sample in wave 3 due to budgetary constraints (National Statistical Office, 2020). The main agricultural season in Malawi ranges from November to July (inclusive), according to FEWS.

In Mali, data from the *Enquête Agricole de Conjoncture Intégrée* (EACI) was assembled from two periods: 2014 and 2017. The smallest tracking unit in Mali is the EA, and households are therefore not followed through time. The survey covers all regions and urban/rural areas, except Kidal (Ministry of Rural Development, 2019). The main agricultural season in Mali ranges from June to December (inclusive), according to FEWS.

In Niger, data were drawn from the *Enquête National sur les Conditions de Vie des Ménages et Agriculture* - ECVM/A) across two periods: 2011 and 2014. Households, including split off households, were tracked across these waves (Ministry of Finance and National Institute of Statistics, 2016). The main agricultural season in Niger ranges from June to December (inclusive), according to FEWS.

In Nigeria, data were assembled from the General Household Survey (GHS) across four periods: 2010/2011, 2012/2013, 2015/2016 and 2018/2019. A partial refresh of the panel was undertaken in wave 4. Split off households were not tracked in Nigeria. While the survey is representative at the regional and urban/rural levels, some areas could not be visited in wave 4 due to security concerns (2018/2019) and this wave is therefore only representative of areas that were accessible (National Bureau of Statistics, 2021a). The main agricultural season in Nigeria ranges from May to December (inclusive) in northern regions and March to November (inclusive) in southern regions, according to FEWS.

In Tanzania, data were assembled from the National Panel Survey (NPS) across five periods: 2008/2009, 2010/2011, 2012/2013, 2014/2015 and 2018/2019. Split off households were tracked in Tanzania (National Bureau of Statistics, 2021b). The main agricultural season (the Masika season) in Tanzania ranges from February to August (inclusive), according to FEWS.

Appendix 2: Sample weights

The six surveys considered are designed to be nationally representative. Sample weights are at the household level. These weights adjust for the propensity of each household to be included in the dataset in each wave, and are needed to make the survey estimates representative of the population at large.

The survey weights used in the analysis were divided by the number of plots in the household, so that households with multiple plots would not be counted multiple times. In addition, weights were rescaled to sum up to the target population in each country-wave. The target population corresponds to the number of households a specific survey is defined to be representative of – usually the national population of households. Weights are therefore calibrated to ensure that they sum to the wave-specific target population even as the sample size is reduced in some specifications, due to the exclusion of non-agricultural households, and because of missing values.

Formally, given a set of households indexed by h (where $h = 1, \dots, N$) in a specific country-wave, where each household is associated with a sample weight W_h. After retaining plots of households that engage in agriculture, and dropping plots with missing values for one or more of the variables used in the model, the total number of households in the country-wave drops from N to n, and weights are adjusted such that:

$$w_h = \frac{W_h}{p_h} \cdot \frac{\sum_{h=1}^{N} W_h}{\sum_{h=1}^{n} W_h}$$

Where p_h denotes the number of plots in household h on which seasonal crops are grown and that are included in the dataset, and w_h is the final adjusted weight.

Appendix 3: Dollar valuations

Valuations of inputs and outputs were done by calculating the median sale or purchase price of the various categories of each input and output variable (for instance, crop variety categories such as maize and sorghum were used in the calculation of output values) in *one* wave in each country. Total output and input values were thus obtained in local currency units (LCUs) and then converted into USD using an exchange rate, and then adjusted to 2020 dollars using a CPI. The CPI and exchange rate data were drawn from World Bank collections of development indicators, made available through the World Bank Open Data Initiative. They consist of yearly time series. Constant prices were chosen to reduce noise resulting from price shocks, which could lead to dynamic changes in relative prices of crops and agricultural inputs, which may interfere with the objective of isolating a productivity time trend. Effectively, constant prices act as time-invariant relative weights of each crop in each country, to enable the aggregation of different crops at the plot (or household, for example) level. However, this choice may miss the real productivity impacts resulting from farmers responding to longer-term relative price changes. The analysis was therefore replicated using wave- and region-specific prices, deflated to current USD.

Appendix 4: Modification of GPS coordinates

The LSMS-ISA surveys follow a spatial de-identification methodology developed by the DHS, whereby household coordinates are averaged at the EA-level and a random offset is applied. An offset range of 0-2 km is used for urban areas, while a range of 0-5 km is used in rural areas (where communities are more dispersed, and risk of disclosure may be higher). An additional 0-10 km offset for 1% of rural clusters (10% in Mali) effectively increases the known range for all rural points to 10 km while introducing only a small amount of noise (Central Statistical Agency and Living Standards Measurement Study (LSMS), World Bank, 2021; Ministry of Finance and National Institute of Statistics, 2016; Ministry of Rural Development, 2019; National Bureau of Statistics, 2021a, 2021b; National Statistical Office, 2020).

Appendix 5: further models

For each household h, agricultural productivity was estimated in the following form (Model 3):

$$\ln\left(\frac{Y_{ht}}{L_{ht}}\right) = \alpha + \beta year_t + \sum_{j=1}^{J} \gamma_j \ln\left(\frac{I_{jht}}{L_{ht}}\right) + \sum_{l=1}^{K} \delta_l \left(X_{lht}\right) + f(W_{ht}) + \theta M_{ht} + C_h + \varepsilon_{ht} \quad (3)$$

Aggregating to the household level also allows the estimation of a fixed effects model (Model 4). In this specification, the intercept varies from one household to the next. This can be written as:

$$\ln\left(\frac{Y_{ht}}{L_{ht}}\right) = \alpha_h + \beta year_t + \sum_{j=1}^{J} \gamma_j \ln\left(\frac{I_{jht}}{L_{ht}}\right) + \sum_{l=1}^{K} \delta_l \left(X_{lht}\right) + f(W_{ht}) + \theta M_{ht} + C_h + \varepsilon_{ht} \quad (4)$$

Alternatively, aggregating to the plot manager level provides the opportunity to estimate the following fixed effects specification, where plot managers are indexed by m (Model 5):

$$\ln\left(\frac{Y_{mt}}{L_{mt}}\right) = \alpha_m + \beta year_t + \sum_{j=1}^{J} \gamma_j \ln\left(\frac{I_{jmt}}{L_{mt}}\right) + \sum_{l=1}^{K} \delta_l \left(X_{lmt}\right) + f(W_{mt}) + \theta M_{mt} + C_m + \varepsilon_{mt} \quad (5)$$

Similarly, the following cluster-level fixed effects model is specified (Model 6):

$$\ln\left(\frac{Y_{ct}}{L_{ct}}\right) = \alpha_c + \beta year_t + \sum_{j=1}^{J} \gamma_j \ln\left(\frac{I_{jct}}{L_{ct}}\right) + \sum_{l=1}^{K} \delta_l \left(X_{lct}\right) + f(W_{ct}) + \theta M_{ct} + C_c + \varepsilon_{ct} \quad (6)$$

Standard errors are clustered at the enumeration area level, accounting for correlated shocks. Standard errors also take into account the surveys' sampling designs (Heeringa et al., 2020). While standard errors are linearized in most specifications, they are bootstrapped in fixed effects models (Kolenikov, 2010).

Additionally, we run a specification with an added interaction on the time trend, to explore the difference in trends across plots managed by men and women. We multiply the time trend by a dummy variable equal to 1 if the plot manager is reported to be female. We can write this as:

$$\ln\left(\frac{Y_{it}}{L_{it}}\right) = \alpha + \beta year_t + \beta_2 year_t \times F_{it}$$
$$+ \sum_{j=1}^{J} \gamma_j \ln\left(\frac{I_{jit}}{L_{it}}\right) + \sum_{l=1}^{K} \delta_l \left(X_{lit}\right) + f(W_{it}) + \theta M_{it} + C_i + \varepsilon_{it} \quad (7)$$

Table A. 1. Distribution of waves across countries and years

Year	Ethiopia	Malawi	Mali	Nigeria	Niger	Tanzania
2004						
2005						
2006						
2007						
2008						Wave 1
2009		Wave 1				
2010		Wave 1		Wave 1		Wave 2
2011	Wave 1				Wave 1	
2012	Wave 1	Wave 2		Wave 2		Wave 3
2013	Wave 2	Wave 2				
2014	Wave 2		Wave 1		Wave 2	Wave 4
2015	Wave 3	Wave 3		Wave 3		
2016	Wave 3	Wave 3				
2017			Wave 2			
2018	Wave 4	Wave 4		Wave 4		
2019	Wave 4	Wave 4				Wave 5
2020						

Table A. 2. Rate of missing values by variable in the plot-level survey dataset

Variable	Missing (%)	Unit of observation
Input variables		
Seed value in constant USD/ha	8.8	Plot
Inorganic fertilizer value in constant USD/ha	1.8	Plot
Hired labor-days in constant USD/ha	1.5	Plot
Non-hired labor days /ha	1.6	Plot
Agricultural assets index (PCA)	0.5	Plot
Plot controls		
Pesticides used on plot? (Y/N)	1.5	Plot
Organic fertilizers used on plot? (Y/N)	1.6	Plot
Plot irrigated? (Y/N)	1.2	Plot
Crop intercropped on plot? (Y/N)	0.8	Plot
Crop shock on plot? (Y/N)	0.3	Plot
Does the plot manager have formal education? (Y/N)	2.0	Plot
Is the plot manager female? (Y/N)	1.3	Plot
Age of the plot manager	1.7	Plot
Is the plot owned by the household? (Y/N)	1.0	Plot
Does the plot contain a missing harvest value? (Y/N)	0.0	Plot
Household controls		
Household shock on plot? (Y/N)	0.4	Household
Household owns livestock? (Y/N)	0.4	Household
Household size	0.3	Household
Does the household have access to electricity? (Y/N)	0.3	Household
Is the household classified as urban? (Y/N)	0.0	Household
Geospatial variables		
Agro-ecological zone	1.5	Household or EA
Distance to the closest road	1.4	Household or EA
Distance to the closest population center	1.4	Household or EA
Elevation	1.9	Plot, Household or EA
Soil fertility index	2.6	Household or EA
Weather controls		
Temperature		
Seasonal average of mean monthly temperature (T) *****	0.3	Cluster
Sd of T over season	0.3	Cluster
Seasonal minimum of T	0.3	Cluster
Seasonal maximum of T	0.3	Cluster
Deviation of average T from historic seasonal levels	0.3	Cluster
Number of months in season where T <15C	0.3	Cluster
Number of months in season where T >25C	0.3	Cluster
Number of months in season where T >30C	0.3	Cluster
Number of months in season where T >35C	0.3	Cluster
Seasonal maximum mean daily temperature (t)	0.3	Cluster
Seasonal minimum t	0.3	Cluster
Seasonal maximum of monthly minimum t	0.3	Cluster
Seasonal minimum of monthly minimum t	0.3	Cluster
Seasonal maximum of max monthly range of t	0.3	Cluster
Precipitation		
Seasonal cumulative precipitation *****	0.3	Cluster
Sd of monthly cumulative precipitation (P) over season	0.3	Cluster
Seasonal minimum of P	0.3	Cluster
Seasonal maximum of P	0.3	Cluster
Nb months where cumulative precip> 95th percentile of historical level of P in season	0.3	Cluster
Nb months where cumulative precip > 99th percentile of historical level of P in season	0.3	Cluster
Nb months where P < 5th percentile of historical level of P in season	0.3	Cluster
Nb months where P < 1th percentile of historical level of P in season	0.3	Cluster
Deviation of average P from historic seasonal levels	0.3	Cluster

Number of months in season with no precip	0.3	Cluster
Maximum cumulative daily precipitation (p) in season	0.3	Cluster
Maximum cumulative 5-day precipitation in season	0.3	Cluster
Precipitation intensity index (cumulative precipitation/total number of wet days)	0.3	Cluster
Number of days in season where p > 5mm	0.3	Cluster
Number of days in season where p > 10mm	0.3	Cluster
Number of days in season where p > 20mm	0.3	Cluster
Maximum length (in days) of a dry spell (p <1 mm) in season	0.3	Cluster
Maximum length (in days) of a wet spell in season	0.3	Cluster

Note: This table lists variables used in the preferred statistical specification. Only a subset of the listed geospatial variables and weather controls were included, chosen by the LASSO algorithm. Leads and lags of weather variables followed by a star (*) are provided in the dataset.

Table A. 3. Descriptive statistics – Output and selected inputs

COUNTRY	WAVE	Harvest value (constant 2020 USD/ha)			Plot area (ha)			Seed value (constant USD/ha)			Non-hired labor days (days/ha)		
		Med	Mean	Sd	Med	Mean	Sd	Med	Mean	Sd	Med	Mean	Sd
Ethiopia	1	361	605	30	0.10	0.19	0.03	28	64	5	239	678	58
Ethiopia	2	378	1034	71	0.10	0.27	0.05	37	89	6	252	1304	126
Ethiopia	3	350	998	76	0.10	0.19	0.01	29	60	4	228	1414	159
Ethiopia	4	412	1043	90	0.09	0.17	0.01	41	130	15	267	1258	157
Malawi	1	314	486	17	0.31	0.38	0.01	16	668	74	171	249	8
Malawi	2	379	661	29	0.28	0.39	0.02	22	41	2	203	334	15
Malawi	3	261	422	25	0.28	0.37	0.02	18	35	4	206	286	13
Malawi	4	268	434	18	0.25	0.33	0.01	20	36	2	216	353	16
Mali	1	184	570	32	0.78	3.03	0.27	5	27	2	83	338	26
Mali	2	170	456	18	1.00	1.77	0.05	6	25	1	114	336	20
Niger	1	28	126	16	1.21	2.31	0.16	7	22	2	28	113	12
Niger	2	81	226	20	1.25	2.24	0.14	7	15	1	32	88	8
Nigeria	1	1176	7034	547	0.27	0.65	0.05	49	636	50	157	1160	102
Nigeria	2	995	3391	261	0.27	0.62	0.06	85	1243	157	520	2225	162
Nigeria	3	959	2962	219	0.27	0.56	0.05	33	477	41	451	1550	128
Nigeria	4	707	1717	74	0.31	0.66	0.06	13	470	69	160	473	28
Tanzania	1	115	211	9	0.61	1.17	0.08	10	22	2	98	190	12
Tanzania	2	136	253	11	0.57	1.21	0.07	12	30	3	95	179	8
Tanzania	3	125	249	10	0.58	1.26	0.07	16	30	1	98	165	6
Tanzania	4	183	286	22	0.50	1.05	0.15	18	31	4	101	175	18
Tanzania	5	145	261	21	0.40	1.25	0.20	17	34	3	22	64	8

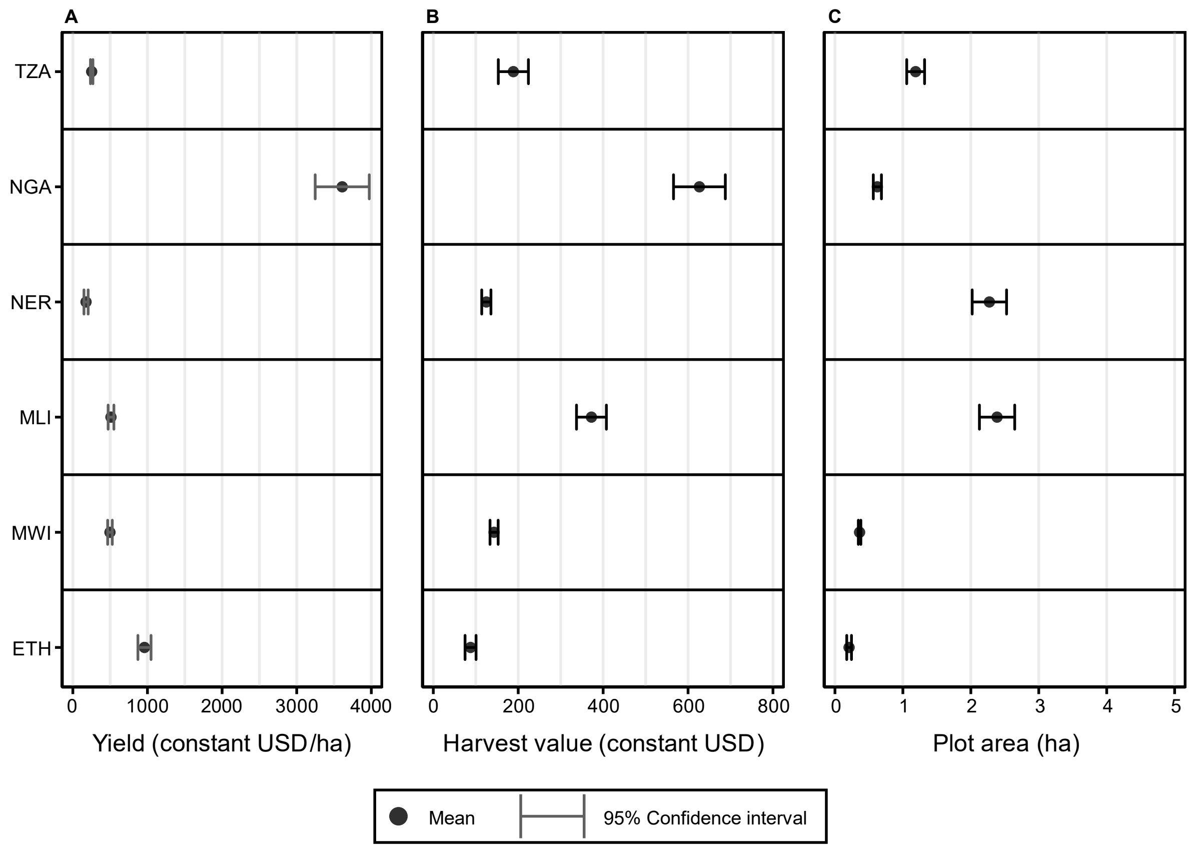
Note: All reported means, medians, and standard deviations are weighted. All variables shown have been winsorized as described above.

Table A. 4. Descriptive statistics – selection of further controls

COUNTRY	**WAVE**	Mean household size	Mean age of plot manager	Rate of irrigated plots (%)	Rate of plots suffering from a crop shock during ag season (%)	Mean distance to nearest population center (km)	Mean elevation (m)	Mean longest wet spell in ag. season (number of days)	Mean of average monthly temperature in ag. Season (Celsius)
Ethiopia	1	5	44	2.3%	46.5%	36	1985	9	19
Ethiopia	2	5	45	2.2%	38.0%	35	2022	11	19
Ethiopia	3	5	47	2.3%	56.1%	36	2030	8	20
Ethiopia	4	5	46	2.4%	51.3%	27	2102	11	19
Malawi	1	5	42	0.7%	52.4%	34	901	15	22
Malawi	2	5	44	1.3%	56.2%	34	901	12	22
Malawi	3	5	45	0.6%	73.4%	34	892	10	23
Malawi	4	5	46	0.6%	65.3%	23	892	19	22
Mali	1	11	49	8.1%	29.1%	57	303	5	29
Mali	2	12	50	10.5%	28.3%	60	302	5	29
Niger	1	7	41	1.2%	96.1%	61	340	5	29
Niger	2	7	45	1.5%	51.3%	60	344	5	29
Nigeria	1	6	49	2.9%	5.0%	24	310	9	27
Nigeria	2	6	52	1.9%	9.0%	22	333	10	27
Nigeria	3	7	52	1.8%	5.3%	28	319	8	27
Nigeria	4	6	49	3.0%	8.7%	21	304	9	27
Tanzania	1	5	47	3.3%	57.3%	51	1049	11	21
Tanzania	2	5	48	2.5%	59.8%	52	1042	9	22
Tanzania	3	5	48	2.7%	52.7%	53	1040	10	22
Tanzania	4	5	48	1.5%	37.7%	50	1168	10	22
Tanzania	5	5	49	0.6%	49.3%	50	1197	10	22

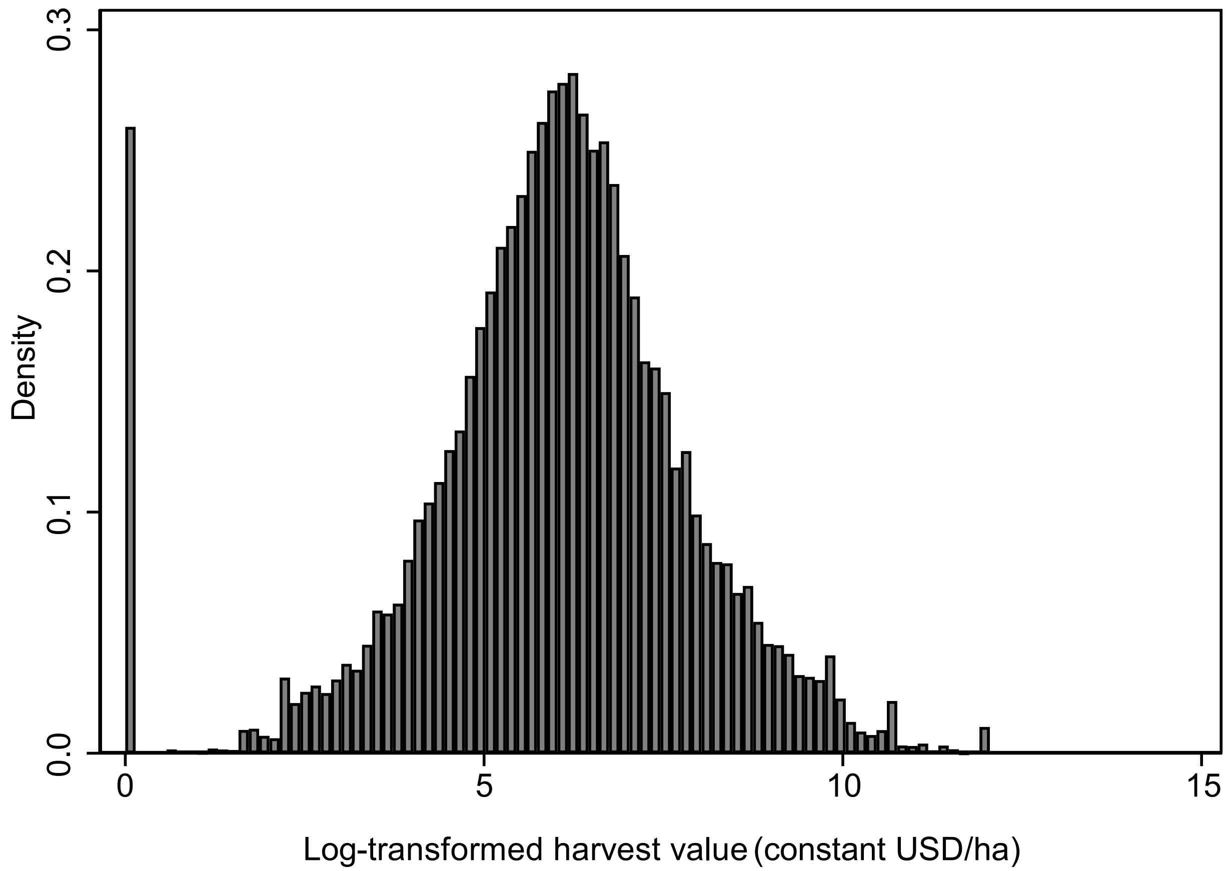
Note: This table presents statistics for a selection of controls included in the analysis. All descriptive statistics reported above are weighted. Household sizes were winsorized at the 99th percentile within each wave.

Figure A. 1. Average plot-level yield, output values and plot areas by country



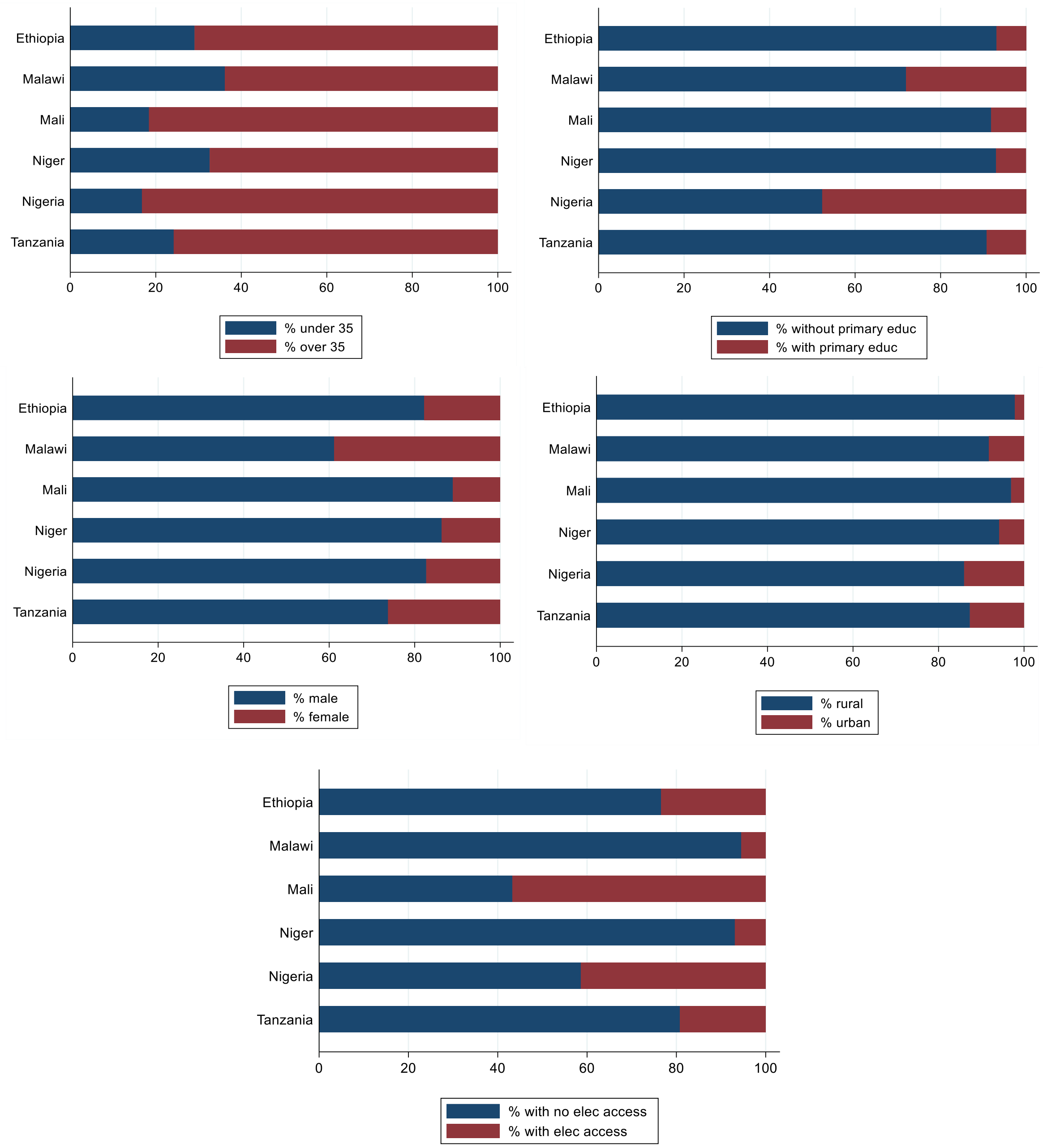
*Note: This figure plots weighted means and confidence intervals for yields (**A**), total harvest value per plot (**B**), and plot area (**C**), in each country included in the sample: Tanzania (TZA), Nigeria (NGA), Niger (NER), Mali (MLI), Malawi (MWI) and Ethiopia (ETH). Panel A presents these statistics for yields (harvest values per hectare), Panel B presents these statistics for total harvest value per plot and Panel C for plot areas. Constant prices are used to value output.*

Figure A. 2. Histogram of yield (harvest value per hectare), log transformed



Note: This figure plots the distribution of output values. Plot-level production is valued using constant prices, log-transformed and incremented by one. Output values are winsorized at the 99th and 1st percentiles, while retaining plots with no output to account for full losses. Sample weights have been applied.

Figure A. 3. Farmer and household characteristics by country



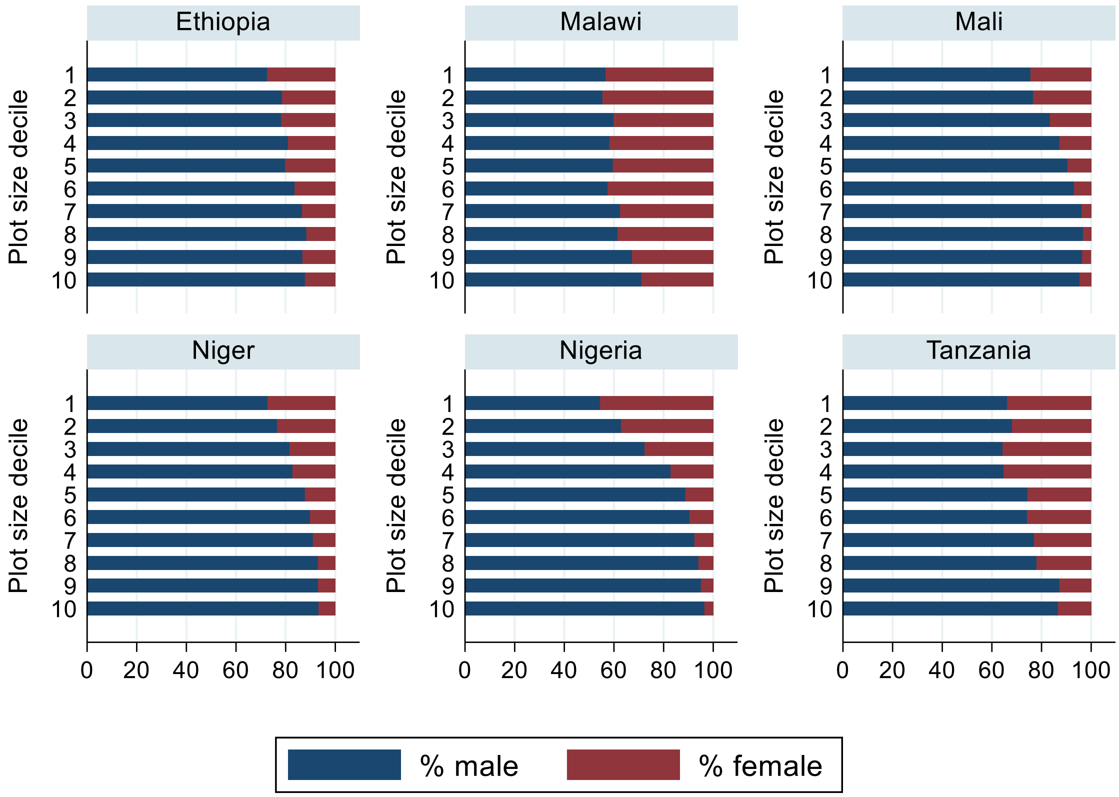
Note: All reported statistics are weighted.

Table A. 5. Farmer and household characteristics overall and by country

	% managed by farmers 35+	% managed by farmers without primary education	% managed by women	% of plots in rural areas	% of plots in households with access to electricity
Pooled sample	76.76%	78.57%	20.63%	90.18%	30.16%
Ethiopia	70.81%	92.88%	17.96%	97.89%	23.44%
Malawi	63.67%	71.30%	39.06%	91.78%	5.47%
Mali	81.58%	91.67%	11.20%	96.97%	56.68%
Niger	65.78%	92.89%	15.21%	94.16%	6.90%
Nigeria	83.20%	51.51%	18.12%	86.01%	41.36%
Tanzania	73.98%	90.12%	27.77%	87.37%	19.08%

Note: All reported statistics are weighted.

Figure A. 4. Percentage of plot observations reporting female/ male managers across plot size deciles, within countries



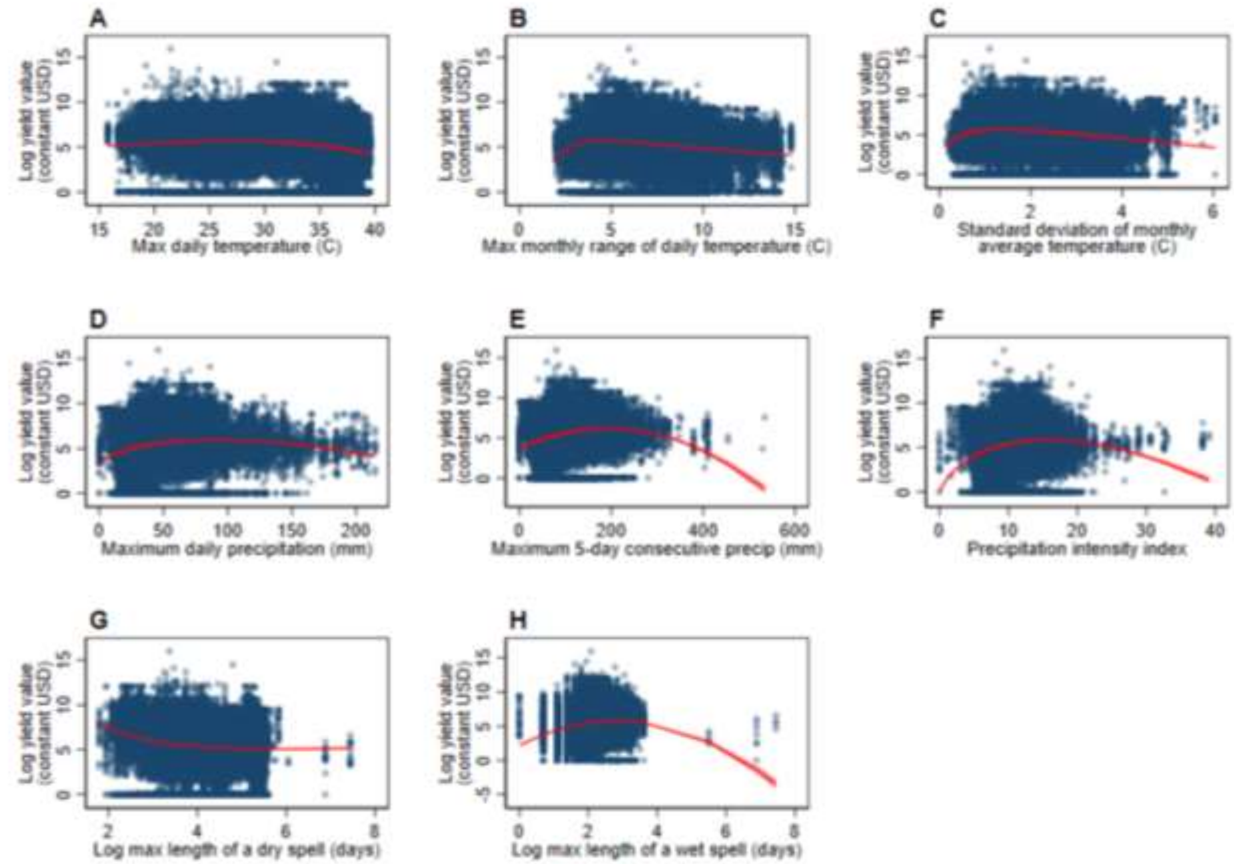
Note: All reported statistics are weighted.

Table A. 6. Correlations between average yields and farmer/household characteristics, table of coefficients

Dependent variable	Coefficient of a regression on logged yield values (in constant USD)
Manager is over 35 years old	-0.0481
Default: under 35	(0.0307)
Manager has completed primary school	0.129***
Default: no primary school	(0.0462)
Manager is female	-0.0636
Default: male	(0.0427)
Urban household	0.0329
Default: rural	(0.0835)
Household has access to electricity	0.0772
Default: no access	(0.0512)
Household dependency ratio	-0.0573***
	(0.0158)

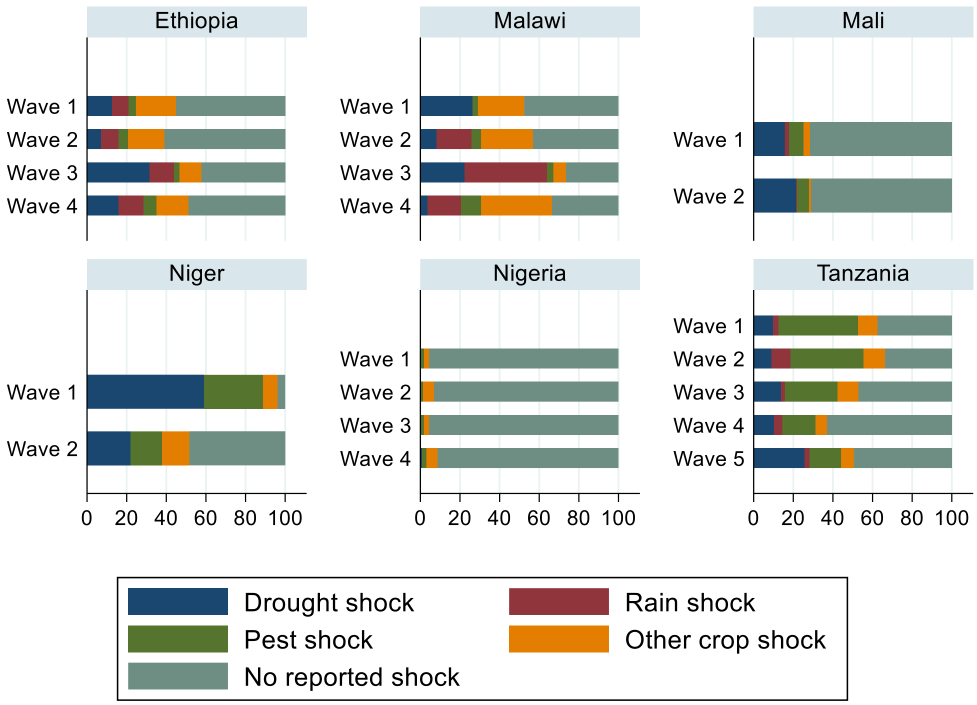
Note: Country fixed effects are included in all regressions

Figure A. 5. Non-linear relationships between yields and weather variables



Note: These graphs plot the relationship between logged yield values (in constant USD) and a set of weather variables. These consist of scatterplots (in blue) as well as a fractional polynomial fit with a 95% confidence interval (in red).

Figure A. 6. Crop shock prevalence and breakdown by country-wave



Note: All reported statistics are weighted.

Table A. 7. Overall productivity growth results

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Prices (valuation method)	Constant USD	Constant USD	Constant USD	Constant USD	Constant USD	Constant USD	Current USD
FE model	No	No	No	Yes	Yes	Yes	No
Level of data aggregation	Plot	Plot	Household	Household	Farmer	Cluster	Plot
Annual time trend	-0.039***	-0.0345***	-0.0170***	-0.0357***	-0.0407***	-0.00651	-0.0555***
	(0.00695)	(0.00649)	(0.00603)	(0.01029)	(0.0115)	(0.0102)	(0.00677)
Plot area (ha)		-0.250***	-0.186***	-0.401***	-0.387***	-0.385***	-0.250***
		(0.0191)	(0.0197)	(0.02629)	(0.0300)	(0.0613)	(0.0196)
Non-hired labor days (per ha)		0.117***	0.137***	0.124***	0.121***	0.130***	0.125***
		(0.0141)	(0.0151)	(0.0164)	(0.0185)	(0.0313)	(0.0146)
Seed value, USD (per ha)		0.157***	0.154***	0.095***	0.102***	0.0776***	0.143***
		(0.0111)	(0.0121)	(0.0221)	(0.0196)	(0.0262)	(0.0105)
Hired labor value, USD (per ha)		0.0534***	0.0500***	0.032***	0.0353***	0.0337**	0.0643***
		(0.00610)	(0.00630)	(0.00789)	(0.00814)	(0.0147)	(0.00711)
Inorg. Fertilizer value, USD (per ha)		0.0729***	0.0737***	0.051***	0.0515***	0.0835***	0.0879***
		(0.00639)	(0.00740)	(0.00891)	(0.00912)	(0.0225)	(0.00734)
Agricultural assets index		0.0644***	0.0605***	0.0492***	0.0502**	0.0447	0.0751***
		(0.0199)	(0.0193)	(0.0197)	(0.0204)	(0.0355)	(0.0198)
Plot & household controls	No	Yes	Yes	Yes	Yes	Yes	Yes
Main crop dummies	No	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weather & Geospatial controls	No	Yes	Yes	Yes	Yes	Yes	Yes
Joint significance of weather and & geospatial controls (P-value)	-	0.00	0.00	0.00	0.00	0.00	0.00
Observations	115,627	115,627	42,504	42,463	47,551	7,739	112,042

Adj. R-squared	0.219	0.513	0.457	0.448	0.408	0.660	0.421

Note: This table provides coefficient estimates for the time trend and inputs of six baseline specifications. Across all these specifications, the dependent variable is log yield (output value per hectare). All input variables are also log transformed, except the agricultural assets index. The table includes the P-value of a joint significance test of all weather and geospatial controls included in the model based on a LASSO algorithm. Country and main crop effects are also included in all specifications. Results consist of specifications with: (1) plot-level data and only a time trend and country fixed effects (2) plot level data and all controls integrated in the baseline model outlined in Section SI.III (3) and (4), household level data (5) farmer (plot manager) level data (6) cluster level data, and (7) plot level data using current prices. Adjusted sampling weights are used across specifications.

Table A. 8. Country level yield trends

	Ethiopia	Malawi	Mali	Niger	Nigeria	Tanzania
	(1)	(2)	(3)	(4)	(5)	(6)
Annual time trend	0.00198	-0.0378***	0.00743	0.353***	-0.0862***	0.00176
	(0.0138)	(0.00710)	(0.0225)	(0.0260)	(0.0108)	(0.0138)
Plot & household controls	No	No	No	No	No	No
Weather & Geospatial controls	No	No	No	No	No	No
Joint significance of weather and & geospatial controls (P – value)	-	-	-	-	-	-
Observations	36,195	17,056	30,817	7,029	17,148	7,383
Adj. R-squared	0.000	0.010	0.000	0.120	0.020	0.000

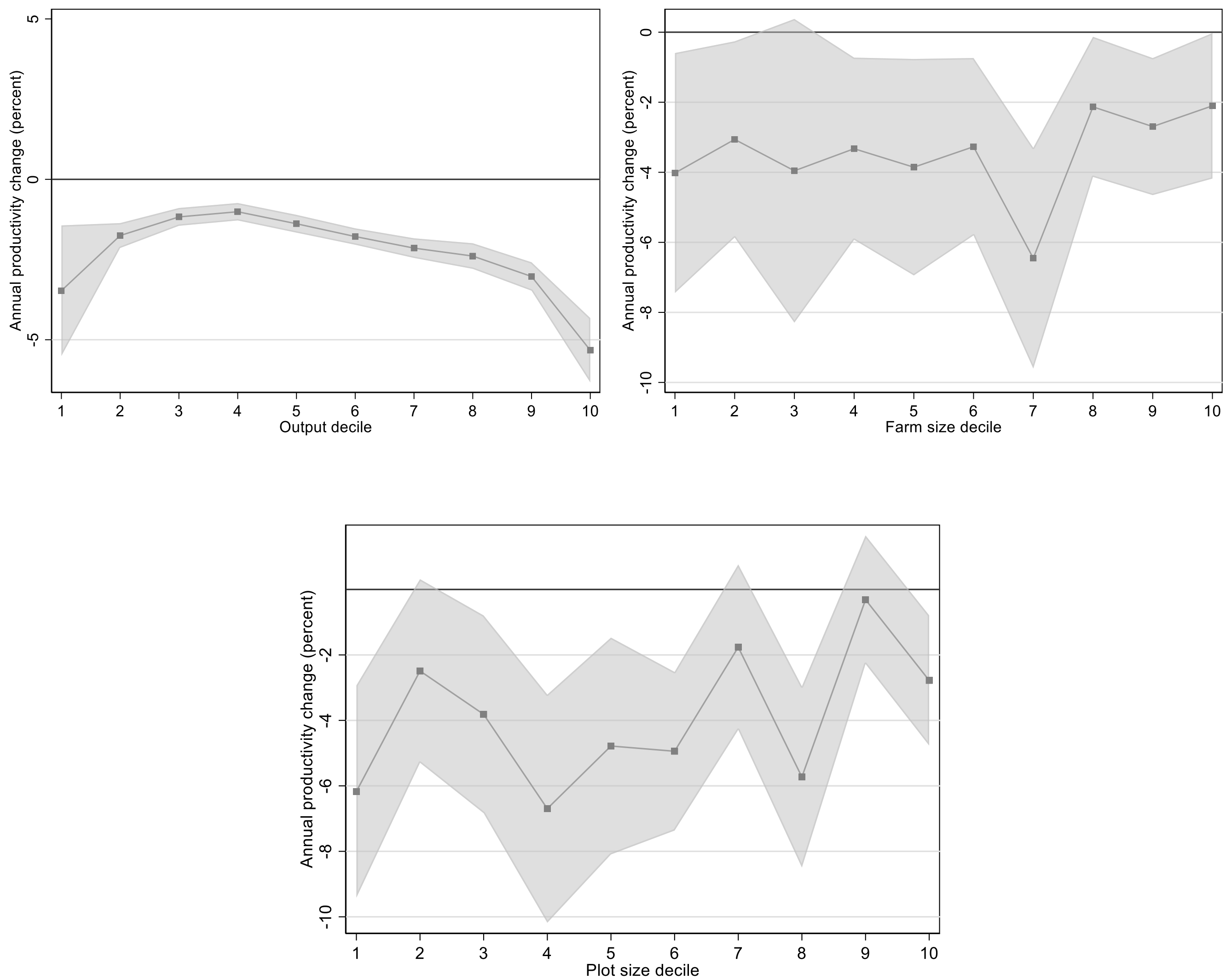
Note: This table presents country-level results of a model where log yields are regressed against an annual time trend and country dummies (Model 1). Adjusted sampling weights are used across all models.

Table A. 9. Country level results – preferred specification

	Ethiopia	Malawi	Mali	Niger	Nigeria	Tanzania
	(1)	(2)	(3)	(4)	(5)	(6)
Annual time trend	0.000	-0.0354***	-0.0174	0.303***	-0.0483***	-0.00371
	(0.0131)	(0.00780)	(0.0251)	(0.0284)	(0.0108)	(0.0120)
Plot area (ha)	0.166***	-0.168***	-0.305***	-0.280***	-0.554***	-0.0812**
	(0.0315)	(0.0235)	(0.0251)	(0.0337)	(0.0230)	(0.0327)
Non-hired labor days (per ha)	0.462***	0.243***	0.257***	0.259***	0.0208	0.175***
	(0.0347)	(0.0202)	(0.0244)	(0.0277)	(0.0140)	(0.0321)
Seed value, USD (per ha)	0.187***	0.0801***	0.155***	0.183***	0.105***	0.425***
	(0.0275)	(0.00968)	(0.0277)	(0.0350)	(0.0132)	(0.0356)
Hired labor value, USD (per ha)	0.0382***	0.0971***	0.0733***	0.106***	0.0424***	0.115***
	(0.0141)	(0.00898)	(0.00876)	(0.0132)	(0.00667)	(0.0119)
Inorg. Fertilizer value, USD (per ha)	0.0647***	0.115***	0.114***	0.0391**	0.0402***	0.0681***
	(0.0108)	(0.00739)	(0.00998)	(0.0169)	(0.00775)	(0.0221)
Agricultural assets index	0.0407	0.116***	0.0103	0.0570**	0.0490*	0.0918***
	(0.0309)	(0.0164)	(0.0121)	(0.0243)	(0.0264)	(0.0324)
Plot & household controls	Yes	Yes	Yes	Yes	Yes	Yes
Country & main crop fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Weather & Geospatial controls	Yes	Yes	Yes	Yes	Yes	Yes
P-value	0.00	0.00	0.00	0.00	0.00	0.00
Observations	36,195	17,056	30,817	7,029	17,148	7,383
Adj. R-squared	0.237	0.336	0.469	0.446	0.408	0.379

Note: This table presents country-level results of a model where log yields are regressed against a full set of baseline controls (Model 2). P-values for a joint significance test of weather and geospatial controls are added. Adjusted sampling weights are used across all models.

Figure A. 7. Estimated coefficients of productivity change across output, plot size and farm size deciles



Note: This figure plots coefficients and 95% confidence intervals of productivity change estimates for the preferred specification, run across different deciles of output values, farm sizes and plot sizes. Deciles were computed within country-waves.

Table A. 10. Differential productivity trends for plots managed by individuals with education vs without education

Dependent variable	**Baseline results (model 2)**	**Annual time trend for plot managers without primary school education**	**Interaction term (annual time trend × education dummy variable),** difference in the annual time trend plots managed by individuals with primary education relative to those without	**Annual time trend for plot managers without primary school education**
	(1)	(2)	(3)	(4)
Pooled sample	NA	-0.0578***	-0.00480	-0.0686***
		(0.0103)	(0.0124)	(0.0263)
Ethiopia	NA	-0.000944	0.00592	0.00498
		(0.0134)	(0.0352)	(0.035)
Malawi	NA	-0.0362***	-5.94e-05	-0.0363***
		(0.00785)	(0.00884)	(0.0099)
Mali	NA	0.00203	-0.00808	-0.006
		(0.0308)	(0.0347)	(0.039)
Niger	NA	0.291***	-0.0142	0.277***
		(0.0319)	(0.0688)	(0.0716)
Nigeria	NA	-0.123***	0.0523	-0.0711**
		(0.0222)	(0.0335)	(0.036)
Tanzania	NA	-0.00480	0.00206	-0.0027
		(0.0124)	(0.0206)	(0.021)

Note: This table plots coefficients of various dependent variables in a modified version of model 2 (with an added interaction, the coefficient of which is reported in column (3)) across different samples. Column 4 plots the estimated effect of the interaction combined with the time trend. Adding a dummy for primary education leads to a further drop in the sample (around 5% of observations drop compared to the baseline, most are contained in Nigeria). Column (1) has been omitted to prevent comparisons of results on two different samples.

Table A. 11. Differential productivity trends for plots with older vs younger managers

Sample	Baseline results (model 2)	Annual time trend for plot managers under 35 years of age	Interaction term (annual time trend × age dummy variable), difference in the annual time trend plots managed by individuals over 35 relative to those under 35	Annual time trend for plot managers over 35 years of age
	(1)	(2)	(3)	(4)
Pooled sample	-0.0345***	-0.0462***	0.0155	-0.0307***
	(0.00649)	(0.0105)	(0.00974)	(0.0066)
Ethiopia	0.000	-0.0116	0.0172	0.0056
	(0.0131)	(0.0166)	(0.0150)	(0.014)
Malawi	-0.0354***	-0.0368***	-0.000692	-0.0375***
	(0.0078)	(0.00934)	(0.00755)	(0.008)
Mali	-0.0174	0.0349	-0.0420	-0.007
	(0.0251)	(0.0357)	(0.0304)	(0.0314)
Niger	0.303***	0.302***	0.00475	0.307***
	(0.0284)	(0.0440)	(0.0389)	(0.0288)
Nigeria	-0.0483***	-0.0689***	0.0207	-0.0482***
	(0.0108)	(0.0192)	(0.0175)	(0.011)
Tanzania	-0.00371	-0.00119	-0.00301	-0.004
	(0.012)	(0.0224)	(0.0230)	(0.0126)

Note: This table plots coefficients of various dependent variables in a modified version of model 2 (with an added interaction, the coefficient of which is reported in column (3)) across different samples. Column 4 plots the estimated effect of the interaction combined with the time trend.

Table A. 12. Time trend in input variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dependent variable	Productivity time trend (Model 1)	Logged plot area (ha)	Logged non-hired labor days	Logged seed value (constant USD)	Logged hired labor value (constant USD)	Logged inorganic fertilizer value (constant USD)	Dummy: used pesticides	Dummy: used organic fertilizer	Logged farm area (ha)	Logged aggregate value of seeds, fertilizers, hired labor (constant USD)	Input index	Number of plots
Pooled sample	-0.039***	-0.00656	-0.0158**	-0.0374***	0.143***	-0.0163	0.00526***	0.0173***	0.0393***	0.0563***	-0.0123***	0.0892***
	(0.00695)	(0.00664)	(0.00795)	(0.00840)	(0.0150)	(0.0134)	(0.00144)	(0.00181)	(0.00710)	(0.00999)	(0.00348)	(0.00756)
Ethiopia	0.00198	-0.0265*	0.0290*	0.0314**	0.124***	0.113***	0.0171***	0.0105***	0.121***	0.0532***	0.0128***	0.195***
	(0.0138)	(0.0150)	(0.0148)	(0.0149)	(0.0292)	(0.0263)	(0.00309)	(0.00407)	(0.0185)	(0.0167)	(0.00300)	(0.0320)
Malawi	-0.0378***	-0.0255***	0.0275***	0.00442	-0.0647***	-0.0264*	0.00170**	0.0136***	-0.0205**	-0.00703	0.000929	0.0341***
	(0.00710)	(0.00460)	(0.00427)	(0.00600)	(0.00654)	(0.0145)	(0.000727)	(0.00201)	(0.00893)	(0.00521)	(0.00584)	(0.00842)
Mali	0.00743	0.0551***	0.118***	0.0486***	0.0720**	-0.0878***	0.00515	0.0222***	0.0707**	0.0499**	0.0262*	-0.0169
	(0.0225)	(0.0177)	(0.0233)	(0.0155)	(0.0359)	(0.0327)	(0.00371)	(0.00669)	(0.0349)	(0.0206)	(0.0156)	(0.0357)
Niger	0.353***	0.0278	-0.00575	-0.0486***	0.0714**	0.0156	0.0106***	0.0115	-0.0368	0.0404**	-0.0156	0.0496
	(0.0260)	(0.0192)	(0.0204)	(0.0168)	(0.0308)	(0.0190)	(0.00261)	(0.00796)	(0.0280)	(0.0201)	(0.0126)	(0.0339)
Nigeria	-0.0862***	0.0252**	0.000511	-0.126***	0.299***	-0.0654***	-0.00101	0.0335***	0.0615***	0.0698***	-0.0270***	0.0804***
	(0.0108)	(0.0106)	(0.0142)	(0.0157)	(0.0257)	(0.0249)	(0.00231)	(0.00269)	(0.0182)	(0.0110)	(0.00608)	(0.00703)
Tanzania	0.00176	-0.0882***	0.0518***	-0.0556***	-0.0237	0.00809***	-0.00423	-0.0882***	0.0216	-0.0115	-0.00929	0.0429***
	(0.0138)	(0.0114)	(0.00818)	(0.0162)	(0.0161)	(0.00282)	(0.00348)	(0.0114)	(0.0138)	(0.0123)	(0.00702)	(0.00780)

Note: This table presents time trend coefficients for a set of regressions corresponding to model 1, where yields have been replaced by various inputs as dependent variables Adjusted sampling weights are used across all models.

Table A. 13. Time trend in input variables, full set of control variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dependent variable	Productivity time trend (Model 2)	Logged plot area (ha)	Logged non-hired labor days	Logged seed value (constant USD)	Logged hired labor value (constant USD)	Logged inorganic fertilizer value (constant USD)	Dummy: used pesticides	Dummy: used organic fertilizer	Logged farm area (ha)	Logged aggregate value of seeds, fertilizers, hired labor (constant USD)	Input index	Number of plots
Pooled sample	-0.0345***	-0.0121**	-0.0195***	-0.0199***	0.108***	-0.0293***	0.00443***	0.0163***	0.0204***	0.0478***	-0.0137***	0.105***
	(0.00649)	(0.00495)	(0.00612)	(0.00630)	(0.0128)	(0.0104)	(0.00132)	(0.00172)	(0.00346)	(0.00362)	(0.00233)	(0.00905)
Ethiopia	0.000	-0.0188*	-0.00953	0.0262***	0.0594**	0.0968***	0.0135***	0.00415	0.0131***	0.0704***	-0.000547	0.217***
	(0.0131)	(0.00984)	(0.00936)	(0.0250)	(0.0234)	(0.00301)	(0.00421)	(0.00421)	(0.00434)	(0.0124)	(0.00282)	(0.0382)
Malawi	-0.0354***	-0.0152***	-0.000233	-0.0205**	-0.0893***	-0.0254	0.00221**	0.0155***	0.00817**	0.0224***	-0.0128***	0.0625***
	(0.0078)	(0.00572)	(0.00625)	(0.00962)	(0.0112)	(0.0184)	(0.00109)	(0.00312)	(0.00411)	(0.00465)	(0.00375)	(0.0102)
Mali	-0.0174	0.108***	0.193***	0.0133	0.124***	-0.118**	-0.00478	0.0370***	0.0478**	-0.0231	0.00967	-0.137**
	(0.0251)	(0.0188)	(0.0301)	(0.0163)	(0.0463)	(0.0456)	(0.00524)	(0.0103)	(0.0208)	(0.0190)	(0.0147)	(0.0656)
Niger	0.303***	0.0655**	0.0121	-0.0238	0.0205	0.0155	0.00809**	-0.0154	-0.0445*	0.0633**	0.0331**	0.0550
	(0.0284)	(0.0266)	(0.0347)	(0.0216)	(0.0469)	(0.0413)	(0.00349)	(0.0116)	(0.0234)	(0.0256)	(0.0141)	(0.0480)
Nigeria	-0.0483***	0.0209**	0.0187	-0.0773***	0.256***	-0.0668***	-0.00582**	0.0337***	0.0184**	0.0456***	-0.0152***	0.0754***
	(0.0108)	(0.00822)	(0.0121)	(0.0138)	(0.0262)	(0.0211)	(0.00259)	(0.00267)	(0.00799)	(0.00486)	(0.00410)	(0.00903)
Tanzania	-0.00371	-0.0533***	-0.118***	0.0592***	-0.128***	-0.0235	0.00695***	-0.00433	0.0153***	0.0233***	-0.00740**	0.0412***
	(0.012)	(0.00697)	(0.00778)	(0.00650)	(0.0159)	(0.0176)	(0.00251)	(0.00368)	(0.00344)	(0.00678)	(0.00326)	(0.00828)

Note: This table presents time trend coefficients for a set of regressions corresponding to model 2, where yields have been replaced by various inputs as dependent variables Adjusted sampling weights are used across all models.

Table A. 14. Time trend in control variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent variable	Productivity time trend (Model 1)	Dummy: household owns livestock	Dummy: household grows perennial crops	Dummy: intercropped plot	Number of seasonal crops on plot	Dummy: crop shock	Dummy: female plot manager	Dummy: plot manager over 35	Dummy: plot manager completed primary school
Pooled sample	-0.039***	-0.0100***	-0.00389*	-0.0169***	-0.0330***	0.000788	0.00393**	0.00503***	0.00547***
	(0.00695)	(0.00189)	(0.00216)	(0.00210)	(0.00408)	(0.00165)	(0.00153)	(0.00150)	(0.00154)
Ethiopia	0.00198	-0.00898***	0.00414	-0.00373	0.00570**	0.0154***	0.00371	0.00388	0.00444**
	(0.0138)	(0.00235)	(0.00668)	(0.00508)	(0.00269)	(0.00539)	(0.00250)	(0.00331)	(0.00198)
Malawi	-0.0378***	0.00224	-0.000348	0.0139***	0.0459***	0.0186***	0.0157***	0.0156***	-0.00461*
	(0.00710)	(0.00309)	(0.00370)	(0.00319)	(0.00696)	(0.00292)	(0.00223)	(0.00186)	(0.00252)
Mali	0.00743	0.00955*	-0.0256***	-0.00212	-0.0155***	0.00132	0.000268	0.00543	0.00453
	(0.0225)	(0.00520)	(0.00374)	(0.00292)	(0.00253)	(0.00682)	(0.00395)	(0.00395)	(0.00317)
Niger	0.353***	0.0367***	0.00696**	0.0312***	0.0803***	-0.149***	-0.00666	0.0298***	0.0142***
	(0.0260)	(0.00655)	(0.00324)	(0.0100)	(0.0196)	(0.0104)	(0.00488)	(0.00462)	(0.00462)
Nigeria	-0.0862***	-0.0127***	-0.00292	-0.0300***	-0.0693***	0.00361***	0.00328	-0.000976	0.0364***
	(0.0108)	(0.00314)	(0.00262)	(0.00297)	(0.00728)	(0.00133)	(0.00235)	(0.00229)	(0.00785)
Tanzania	0.00176	-0.0127***	-0.00292	-0.0300***	-0.0693***	0.00361***	0.00328	-0.000976	0.0364***
	(0.0138)	(0.00314)	(0.00262)	(0.00297)	(0.00728)	(0.00133)	(0.00235)	(0.00229)	(0.00785)

Note: This table presents time trend coefficients for a set of regressions corresponding to model 1, where yields have been replaced by various controls as dependent variables. Adjusted sampling weights are used across all models.

Table A. 15. Time trend in control variables, full set of controls

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent variable	Productivity time trend (Model 2)	Dummy: household owns livestock	Dummy: household grows perennial crops	Dummy: intercropped plot	Number of seasonal crops on plot	Dummy: crop shock	Dummy: female plot manager	Dummy: plot manager over 35	Dummy: plot manager completed primary school
Pooled sample	-0.0345***	-0.00793***	-0.00600***	-0.0161***	-0.00659**	-0.000907	0.00631***	0.00111	8.42e-05
	(0.00649)	(0.00164)	(0.00202)	(0.00182)	(0.00282)	(0.00185)	(0.00135)	(0.00111)	(0.00164)
Ethiopia	0.000	-0.0115***	-0.00378	-0.00645	0.00343	0.00869	0.00615**	0.00490*	0.000383
	(0.0131)	(0.00289)	(0.00657)	(0.00481)	(0.00245)	(0.00596)	(0.00302)	(0.00263)	(0.00210)
Malawi	-0.0354***	0.000395	-0.0190**	0.00845**	0.00340	0.0148***	0.0189***	0.00879***	-0.00319
	(0.0078)	(0.00561)	(0.00737)	(0.00373)	(0.00544)	(0.00523)	(0.00405)	(0.00224)	(0.00337)
Mali	-0.0174	-0.00454	0.00298	-0.00358	-0.0184***	0.0175*	0.0114**	0.000148	0.00191
	(0.0251)	(0.00869)	(0.00447)	(0.00691)	(0.00349)	(0.0104)	(0.00452)	(0.00593)	(0.00317)
Niger	0.303***	0.0152	0.000685	-0.00565	-0.0262	-0.160***	-0.00373	0.0178**	0.0123**
	(0.0284)	(0.0102)	(0.00641)	(0.0132)	(0.0218)	(0.0127)	(0.0100)	(0.00699)	(0.00476)
Nigeria	-0.0483***	-0.00110	0.00117	-0.0181***	-0.0151***	0.00516***	0.0135***	-0.00423**	0.0186**
	(0.0108)	(0.00326)	(0.00240)	(0.00282)	(0.00505)	(0.00164)	(0.00228)	(0.00174)	(0.00731)
Tanzania	-0.00371	-0.0122***	-0.0142***	-0.0133***	0.0118**	-0.0186***	-0.00290	0.000689	-0.00933***
	(0.012)	(0.00382)	(0.00338)	(0.00417)	(0.00571)	(0.00430)	(0.00370)	(0.00290)	(0.00233)

Note: This table presents time trend coefficients for a set of regressions corresponding to model 2, where yields have been replaced by various controls as dependent variables. Adjusted sampling weights are used across all models.

Table A. 16. Evolution of soil conditions

	(1)	(2)	(3)	(4)	(6)	(7)	(8)
Dependent variable	Dummy: no constraint for nutrient availability	Dummy: no constraint for nutrient retention capacity	Dummy: no constraint for rooting conditions	Dummy: no constraint for oxygen availability to roots	Dummy: no excess salts	Dummy: no toxicity	Dummy: no workability (field management) constraint
Pooled sample, model 1	-0.00280	-0.000202	-0.00154	0.000654	-0.00120	-0.00157	-0.00143
	(0.00341)	(0.00346)	(0.00353)	(0.00307)	(0.00154)	(0.00129)	(0.00326)
Pooled sample, model 2	-0.00269	2.56e-05	0.00154	0.000412	-0.000581	-0.000550	0.000441
	(0.00341)	(0.00347)	(0.00347)	(0.00301)	(0.00132)	(0.00101)	(0.00322)

Note: This table presents time trend coefficients for a set of regressions corresponding to model 1 and model 2, where yields have been replaced by various measures of soil quality as dependent variables. Adjusted sampling weights are used across all models.

Table A. 17. Varying sample composition: omitted countries

		Omitted country					
	Baseline (Model 2)	Ethiopia	Malawi	Mali	Niger	Nigeria	Tanzania
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Annual time trend	-0.0345***	-0.0429***	-0.0346***	-0.0345***	-0.0349***	-0.00500	-0.0399***
	(0.00649)	(0.00777)	(0.00709)	(0.00651)	(0.00654)	(0.00784)	(0.00757)
Inputs, plot & household controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Main crop FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weather & Geospatial controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
P-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Observations	115,628	79,433	98,572	84,811	108,599	98,480	108,245
Adj. R-squared	0.414	0.493	0.417	0.412	0.399	0.310	0.377

Note: This table plots results from a set of specifications that are equal to that of Table 2., col (1), but on a varying set of samples. In each sample, a specified country is dropped. P-values for a joint significance test of weather and geospatial controls are added. Adjusted sample weights are used across all specifications.

Table A. 18. Varying sample composition: omitted main crop types

	Omitted crop type									
	None (Model 2)	Barley	Beans/ peas/ lentils/peanuts	Maize	Millet	Nuts	Rice	Sorghum	Tubers/ root crops	Wheat
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Annual time trend	-0.0345***	-0.0356***	-0.0322***	-0.0332***	-0.0283***	-0.0346***	-0.0341***	-0.0228***	-0.0549***	-0.0348***
	(0.00649)	(0.00651)	(0.00779)	(0.0102)	(0.00692)	(0.00648)	(0.00656)	(0.00652)	(0.00783)	(0.00655)
Inputs, plot & household controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Main crop FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weather & Geospatial controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
P-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Observations	115,628	112,326	86,245	79,130	97,579	109,149	109,086	94,011	106,333	112,022
Adj. R-squared	0.414	0.412	0.414	0.387	0.409	0.415	0.422	0.399	0.408	0.412

Note: This table plots results from a set of specifications that are equal to that of Table 2., col (1), but on a varying set of samples. In each sample, plots with a specified main crop type are dropped (main crops are defined as crops with the highest value on the plot). P-values for a joint significance test of weather and geospatial controls are added. Adjusted sampling weights are used across all specifications.

Table A. 19. Alternative productivity measures

		Alternative productivity measures	
	Baseline (Model 2)	Per labor-day	Per seed USD
	(1)	(2)	(3)
Annual time trend	-0.0345***	-0.0334***	-0.0296***
	(0.00649)	(0.00648)	(0.00649)
Inputs, Plot & household controls	Yes	Yes	Yes
Main crop dummies	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes
Weather & Geospatial controls	Yes	Yes	Yes
P-value	0.00	0.00	0.00
Observations	115,628	115,628	114,416
Adj. R-squared	0.414	0.401	0.497

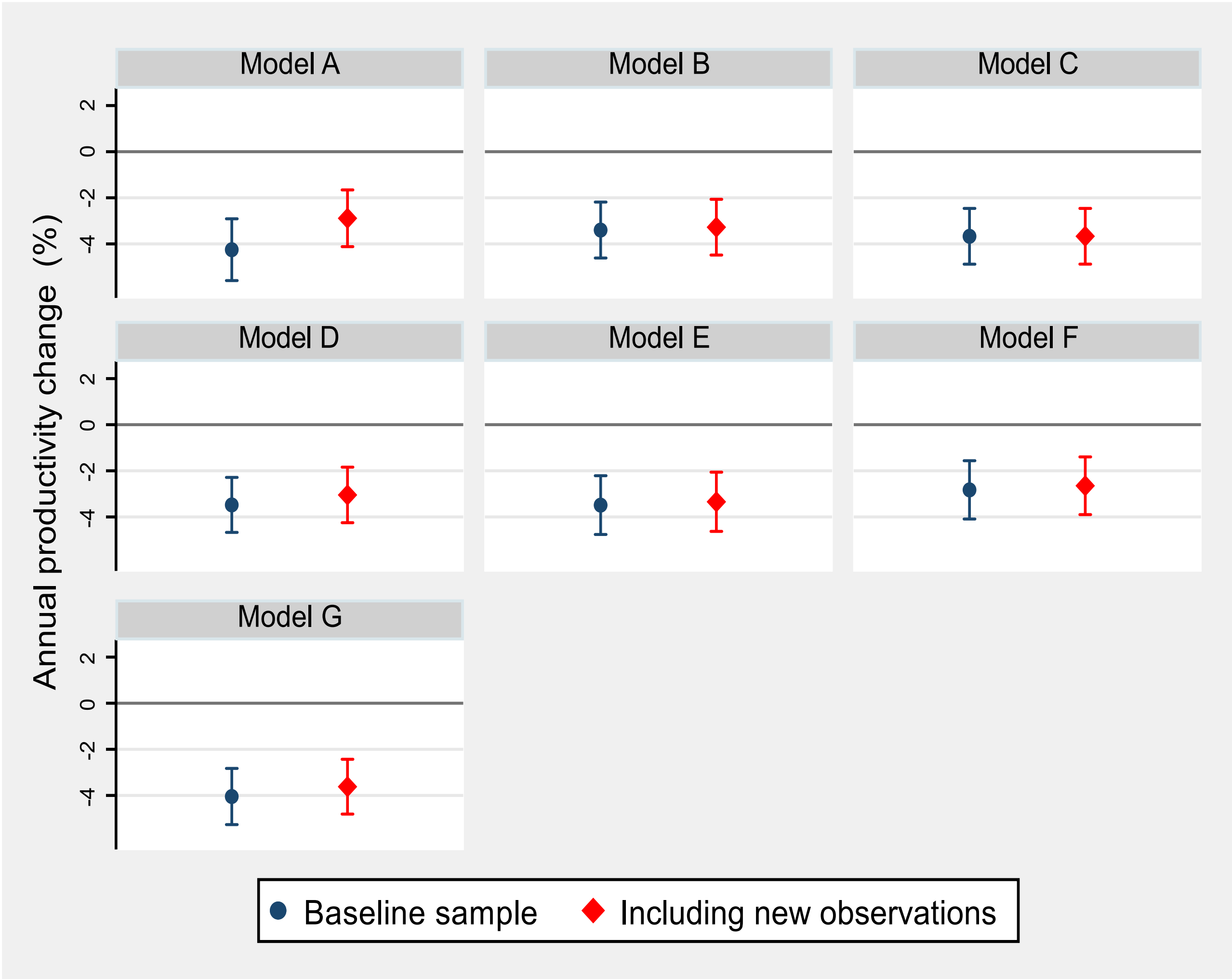
Note: This table presents results of specifications where inputs and outputs are expressed in per labor-day and per seed USD terms ((2) and (3) respectively) instead of per hectare terms. Adjusted sample weights are used across all specifications.

Table A. 20. Alternative outlier corrections

	Winsorisation		Trim		Median replacement	
Percentile	99^{th}	95^{th}	99^{th}	95^{th}	99^{th}	95^{th}
	(1)	(2)	(3)	(4)	(5)	(6)
Annual time trend	-0.0345***	-0.0330***	-0.0172***	-0.00642	-0.0332***	-0.0288***
	(0.00649)	(0.00631)	(0.00483)	(0.00450)	(0.00655)	(0.00581)
Inputs, plot & household controls	Yes	Yes	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes	Yes	Yes
Weather & Geospatial controls	Yes	Yes	Yes	Yes	Yes	Yes
P-value	0.00	0.00	0.00	0.00	0.00	0.00
Observations	115,628	115,628	109,281	104,826	115,628	115,628
Adj. R-squared	0.414	0.412	0.463	0.386	0.400	0.377

Note: This table presents results with a set of different outlier correction methods. Winsorization of the upper tail at the 99^{th} (corresponding to baseline results: Table A. 7, col (2)) and 95^{th} percentiles in columns (1) and (2), trimming at the 99^{th} and 95^{th} percentiles in columns (3) and (4), and median replacement at the 99^{th} and 95^{th} percentiles in columns (7) and (8). All models contain the set of controls used in Model 2. P-values for a joint significance test of weather and geospatial controls are added. Adjusted sample weights are used across all specifications.

Figure A. 8. Missing values 1 – comparison of coefficients across sets of alternative models



Note: Annual time trend coefficients for seven sets of models are plotted here. Each model is run on the baseline sample (that is, the sample of observations with no missing values in the baseline estimation, eg. Model 2) and a sample with observations that were dropped in Model 2 and re-incorporated by dropping sets of controls. Controls in model A only consist only of country fixed effects. Household controls are dropped in model B, weather controls are dropped in model C, geospatial controls are dropped in model D, plot controls are dropped in model E, inputs (except seeds) are dropped in model E, and seed inputs are dropped in model G.

Table A. 21. Missing values 2 – imputation of missing values

	Baseline (Model 2)	Imputed model
	(1)	(2)
Annual time trend	-0.0345***	-0.0365***
	(0.00649)	(0.00615)
Inputs, Plot & household controls	Yes	Yes
Main crop dummies	Yes	Yes
Country fixed effects	Yes	Yes
Weather & Geospatial controls	Yes	Yes
Observations	115,628	134,562
Adj. R-squared	0.414	0.331

Note: This table compares results of the baseline model (Model 2) so that of a model with identical controls but where missing observations are imputed using a random number (col (2)).

5 Bibliography

Alene, A.D., 2010. Productivity growth and the effects of R&D in African agriculture. Agricultural Economics 41, 223–238. https://doi.org/10.1111/j.1574-0862.2010.00450.x

Arthi, V., Beegle, K., De Weerdt, J., Palacios-López, A., 2018. Not your average job: Measuring farm labor in Tanzania. Journal of Development Economics 130, 160–172. https://doi.org/10.1016/j.jdeveco.2017.10.005

Beintema, N., Stads, G.-J., 2017. A comprehensive overview of investments and human resource capacity in African agricultural research (ASTI Synthesis Report). IFPRI.

Belloni, A., Chernozhukov, V., 2011. High Dimensional Sparse Econometric Models: An Introduction. https://doi.org/10.48550/ARXIV.1106.5242

Block, S.A., 2014. The post-independence decline and rise of crop productivity in sub-Saharan Africa: measurement and explanations. Oxford Economic Papers 66, 373–396. https://doi.org/10.1093/oep/gpt010

Block, S.A., 1995. The recovery of agricultural productivity in sub-Saharan Africa. Food Policy 20, 385–405. https://doi.org/10.1016/0306-9192(95)00034-C

Calderón, C.A., 2021. Boosting productivity in Sub-Saharan Africa: policies and institutions to promote efficiency. World Bank Group, Washington, DC, USA. https://doi.org/10.1596/978-1-4648-1550-8

Central Statistical Agency, Living Standards Measurement Study (LSMS), World Bank, 2021. Ethiopia Socioeconomic Survey (ESS), ESS Panel II, 2018/2019.

Desiere, S., Jolliffe, D., 2018. Land productivity and plot size: Is measurement error driving the inverse relationship? Journal of Development Economics 130, 84–98. https://doi.org/10.1016/j.jdeveco.2017.10.002

Devarajan, S., 2013. Africa's Statistical Tragedy. Review of Income and Wealth 59, S9–S15. https://doi.org/10.1111/roiw.12013

Dias Avila, A.F., Evenson, R.E., 2010. Chapter 72 Total Factor Productivity Growth in Agriculture, in: Handbook of Agricultural Economics. Elsevier, pp. 3769–3822. https://doi.org/10.1016/S1574-0072(09)04072-9

Evenson, R.E., Fuglie, K.O., 2010. Technology capital: the price of admission to the growth club. J Prod Anal 33, 173–190. https://doi.org/10.1007/s11123-009-0149-3

Fuglie, K., 2015. Accounting for growth in global agriculture. Bio-based and Applied Economics Vol 4 No 3, 201-234 Pages. https://doi.org/10.13128/BAE-17151

Fuglie, K., Gautam, M., Goyal, A., Maloney, W.F., 2019. Harvesting prosperity: technology and productivity growth in agriculture. World Bank Group, Washington.

Fuglie, K.O., 2018. Is agricultural productivity slowing? Global Food Security 17, 73–83. https://doi.org/10.1016/j.gfs.2018.05.001

Fulginiti, L., Perrin, R., Yu, B., 2004. Institutions and agricultural productivity in Sub-Saharan Africa. Agricultural Economics 31, 169–180. https://doi.org/10.1016/j.agecon.2004.09.005

Gollin, D., Hansen, C.W., Wingender, A.M., 2021. Two Blades of Grass: The Impact of the Green Revolution. Journal of Political Economy 129, 2344–2384. https://doi.org/10.1086/714444

Hastie, T., Tibshirani, R., Wainwright, M., 2015. Statistical Learning with Sparsity: The Lasso and Generalizations, 0 ed. Chapman and Hall/CRC. https://doi.org/10.1201/b18401

Headey, D., Alauddin, M., Rao, D.S.P., 2010. Explaining agricultural productivity growth: an international perspective. Agricultural Economics 41, 1–14. https://doi.org/10.1111/j.1574-0862.2009.00420.x

Heeringa, S.G., West, B.T., Berglund, P.A., 2020. Applied survey data analysis. Chapman & Hall/CRC, Boca Raton.

Hsiang, S., 2016. Climate Econometrics. Annu. Rev. Resour. Econ. 8, 43–75. https://doi.org/10.1146/annurev-resource-100815-095343

Jayne, T.S., Muyanga, M., Wineman, A., Ghebru, H., Stevens, C., Stickler, M., Chapoto, A., Anseeuw, W., Westhuizen, D., Nyange, D., 2019. Are medium-scale farms driving agricultural transformation in sub-Saharan Africa? Agricultural Economics 50, 75–95. https://doi.org/10.1111/agec.12535

Jerven, M., Johnston, D., 2015. Statistical Tragedy in Africa? Evaluating the Data Base for African Economic Development. The Journal of Development Studies 51, 111–115. https://doi.org/10.1080/00220388.2014.968141

Karl, T.R., Nicholls, N., Ghazi, A., 1999. CLIVAR/GCOS/WMO Workshop on Indices and Indicators for Climate Extremes Workshop Summary, in: Karl, T.R., Nicholls, N., Ghazi, A. (Eds.), Weather and Climate Extremes. Springer Netherlands, Dordrecht, pp. 3–7. https://doi.org/10.1007/978-94-015-9265-9_2

Kolenikov, S., 2010. Resampling Variance Estimation for Complex Survey Data. The Stata Journal 10, 165–199. https://doi.org/10.1177/1536867X1001000201

Ludena, C.E., Hertel, T.W., Preckel, P.V., Foster, K., Nin, A., 2007. Productivity growth and convergence in crop, ruminant, and nonruminant production: measurement and forecasts. Agricultural Economics 37, 1–17. https://doi.org/10.1111/j.1574-0862.2007.00218.x

Lusigi, A., Thirtle, C., 1997. TOTAL FACTOR PRODUCTIVITY AND THE EFFECTS OF R&D IN AFRICAN AGRICULTURE. J. Int. Dev. 9, 529–538. https://doi.org/10.1002/(SICI)1099-1328(199706)9:4<529::AID-JID462>3.0.CO;2-U

Mérel, P., Gammans, M., 2021. Climate Econometrics: Can the Panel Approach Account for Long-Run Adaptation? American Journal of Agricultural Economics 103, 1207–1238. https://doi.org/10.1111/ajae.12200

Meybeck, M., Green, P., Vörösmarty, C., 2001. A New Typology for Mountains and Other Relief Classes: An Application to Global Continental Water Resources and Population Distribution. Mountain Research and Development 21, 34–45. https://doi.org/10.1659/0276-4741(2001)021[0034:ANTFMA]2.0.CO;2

Michler, J.D., Josephson, A., Kilic, T., Murray, S., 2021. Estimating the Impact of Weather on Agriculture, Policy Research Working Papers. The World Bank. https://doi.org/10.1596/1813-9450-9867

Ministry of Finance, National Institute of Statistics, 2016. Basic Information Document: 2014 National Survey on Household Living Conditions and Agriculture (ECVM/A-2014).

Ministry of Rural Development, 2019. Basic Information Document: Enquete Agricole de Conjoncture Intégrée aux conditions de vie des ménages (EAC-I 2017).

National Bureau of Statistics, 2021a. Basic Information Document: Nigeria General Household Survey–Panel 2018/19.

National Bureau of Statistics, 2021b. Basic Information Document: National Panel Survey (NPS 2019-2020), Extended Panel with Sex-Disaggregated Data.

National Statistical Office, 2020. Basic Information Document: Malawi Integrated Household Panel Survey (IHPS) 2019.

Suri, T., Udry, C., 2022. Agricultural Technology in Africa. Journal of Economic Perspectives 36, 33–56. https://doi.org/10.1257/jep.36.1.33
Tanzania National Bureau of Statistics, 2021. National Sample Census of Agriculture 2019/20.
USDA, 2021. International Agricultural Productivity (database).
World Bank (Ed.), 2020. Poverty and Shared Prosperity 2020: reversals of fortune, Poverty and shared prosperity. World Bank, Washington.
World Programme for the Census of Agriculture 2020, n.d.
Young, A., 2013. Inequality, the Urban-Rural Gap, and Migration*. The Quarterly Journal of Economics 128, 1727–1785. https://doi.org/10.1093/qje/qjt025