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Crop yields fail to rise in smallholder farming systems in sub-Saharan Africa

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Drawing on a harmonized longitudinal dataset covering more than 55,000 smallholder farms in six African countries, we analyze changes in crop productivity 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 UN Sustainable Development Goals. Our analysis measures productivity trends for nationally representative samples of smallholder crop farmers, using detailed data on agricultural inputs and outputs which we integrate with detailed data on local weather and environmental conditions. In spite of government commitments and international efforts to strengthen African agriculture, we find no evidence that smallholder crop productivity improved over this 12-y period. Our preferred statistical specification of total factor productivity (TFP) suggests an overall decline in productivity of −3.5% per year. Various other models we test also find declining productivity in the overall sample, and none of them finds productivity growth. However, the different countries in our sample experienced varying trends, with some instances of growth in some regions. The results suggest that major challenges remain for agricultural development in sub-Saharan Africa. They complement previous analyses that relied primarily on aggregate national statistics to measure agricultural productivity, rather than detailed microdata.

agriculture | agricultural productivity | Africa | agricultural productivity growth | smallholder agriculture

Sixty percent of the world's poor people live in sub-Saharan Africa, and more than 80 percent of Africa's poor lived in rural areas as of 2019 (1). 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 (2). In the 2003 Maputo Declaration on Agriculture and Food Security, African heads of state committed themselves to increased investment in agricultural productivity and rural development. This 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" (3).

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 15 y of the new millennium. Within that total, spending from the CGIAR, a consortium of international agricultural research institutions, reached more than $500 million over this period (4). Additional development funding aimed at improving agricultural productivity more broadly—through irrigation schemes, land titling programs, rural road construction, and a host of other activities—totaled billions more. We cannot easily assess the effectiveness of these investments because we lack any meaningful counterfactual—i.e., we have no way of knowing what the outcomes would have been in the absence of the investments that have been made. However, we can at least quantify productivity outcomes based on careful analysis. In this paper, we report on an effort to measure trends in smallholder productivity using detailed microdata. Our results draw on nationally representative surveys conducted in six African countries and covering a period of more than 10 y. The data report changes in productivity experienced on over 180,000 plot observations from approximately 55,000 different households. For each plot, we observe detailed data on agricultural inputs and outputs. 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 (5).

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 heterogeneity at

Significance

Boosting the productivity of smallholder farmers in low-income countries matters for poverty eradication and the achievement of the Sustainable Development Goals. Smallholder farmers in sub-Saharan Africa represent a significant fraction of the world's poorest people. We harmonize detailed microlevel production data from more than 55,000 smallholder farms in six African countries, covering a period from 2008 to 2019, to present insights on agricultural productivity growth in this critical sector. We find no evidence that smallholder crop productivity improved over this 12-y period; indeed, the evidence points to declining overall productivity, despite instances of modest growth in some regions. The results suggest that major challenges remain for agricultural development in sub-Saharan Africa.

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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. In none of our models do we find a positive and significant overall trend.

These estimates raise concerns for the overall progress of agricultural development in sub-Saharan Africa. They contribute to a literature (6–9) that has previously relied on aggregate national statistics, which have tended to show modest improvements in agricultural total factor productivity (TFP). The two sets of findings are not necessarily inconsistent, so we do not argue that the 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 (10). Overall, however, our estimates suggest a qualitatively different picture of agricultural productivity growth for the observed period (*SI Appendix*, Table S15). One potential source of the differences may lie in the quality of the national statistics; previous research has called attention to inconsistencies and gaps in the data for many countries (11–14). But leaving aside such issues, the inclusion in national statistics of plantation farms and commercial production implies that those data offer a limited picture of the situation facing Africa's smallholder farmers, who continue to account for a large fraction of the world's poor. Our analysis thus complements the previous macrofocused work by drawing on high-quality microdata that cast a light on the smallholder crop sector. Our high-resolution data also allow us to control more fully for localized weather and input use.

Our analysis uses data from the Living Standards Measurement Study–Integrated Surveys on Agriculture (LSMS-ISA) from six countries: Ethiopia, Malawi, Mali, Niger, Nigeria, and Tanzania. These six countries account for approximately 39% of the population of sub-Saharan Africa, and about one-fifth of the world's extreme poor, defined as individuals living on less than $2.15 per day at 2017 PPP (15, 16).

The data cover a period from 2008 to 2019 and include two to five survey rounds per country. The LSMS-ISA surveys are arguably the highest-quality microdatasets for productivity analysis available for sub-Saharan Africa; the survey methods have been subjected to rigorous testing and validation of measurement methods. The data cover agricultural inputs, outputs, and production practices at the level of individual plots; the agricultural variables link to a rich set of household, individual, community, and geographic variables. The surveys are longitudinal, such that communities, households, and individual farms can be tracked across survey rounds, which allows us to use panel econometric methods. Most of the available LSMS-ISA surveys were included in our analysis; countries (and survey waves within countries) were included based on the criterion that they contained a minimum set of key variables to capture outputs and inputs and that they included sufficient georeferencing to control for other factors, including weather, in a consistent and harmonized fashion (*SI Appendix*, section 1.A).

The data are drawn from nationally representative samples of population (using population sampling weights), which implies that they provide accurate representation of the smallholder sector. We note that the data do not represent the entirety of agricultural production in these countries: the sample in general excludes the largest farms and those organized as commercial enterprises. Another limitation is that we focus in this analysis on crop agriculture. Although livestock play a vital role in smallholder livelihoods, there are fundamental difficulties in constructing productivity measures for animal agriculture in low-intensity smallholder systems. The data do, however, provide a richly detailed depiction of smallholder crop agriculture in these six countries. Because development investments and research effort have intensively targeted smallholder crop production, and because this sector is so important for poverty alleviation, we believe that it is valuable to assess productivity trends within this portion of the rural economy.

Results

We report results from several alternative statistical specifications measuring agricultural productivity growth. We first consider the raw time trend of yield in our data using an ordinary least squares (OLS) regression of yields on a linear time variable, with country fixed effects (model 1).

Yield is a relatively simple measure of agricultural productivity. Total factor 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 forms of 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, in model 2, also referred to as our "baseline model," 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. The best predictive weather variables are chosen using a Least Absolute Shrinkage and Selection Operator (LASSO) formula.[*] We then aggregate input and output variables to estimate a farm-level (rather than plot-level) productivity trend in the same way (model 3).

We further implement three models that make analytical use of the longitudinal structure of our data: We aggregate the data to the household-, farmer-, and cluster-level, respectively, and estimate fixed-effect models for each, which control for time-invariant characteristics of farms, farmers, and clusters (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 revalue inputs and outputs using time- and region-specific current prices, rather than constant prices (model 7).

We run all regressions both on the full cross-country sample and for each country separately. The data are weighted by the approximate population size each data point represents, based on each survey's sampling design.

No Growth in Aggregate Productivity. We find no evidence of growth in crop 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 (Fig. 1). The raw time trend of crop yield in our sample is −3.9%, with the 95% 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%).

We estimate a farm-level (rather than plot-level) productivity time trend of −1.6% per year. (95% CI: −2.8% to −0.3%). The household, farmer, and cluster fixed effects models find productivity changes of −3.5% (95% CI: −5.7% to −1.2%), −4.1% (95% CI: −6.3% to −1.8%), and −2.1% (95% CI: −4.4% to 0.1%), 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 (95% CI: −6.9% to −4.2%). The results are qualitatively robust to several additional sensitivity checks (*SI Appendix*), including alternative methods for dealing with

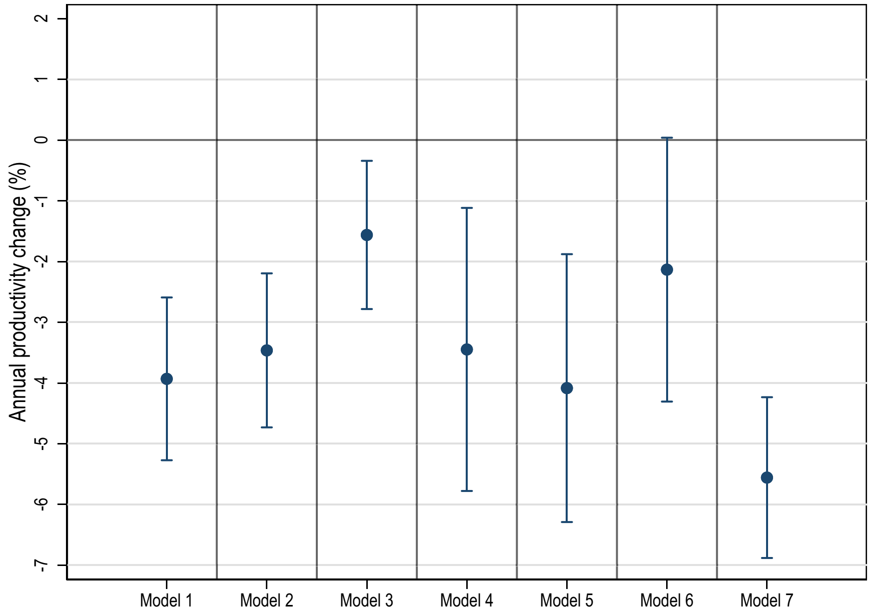

Fig. 1. Estimated coefficients of productivity change across different regression models. This figure plots coefficients and 95% CIs of productivity change estimates from various regression models. Model 1 is a simple regression of yield on a linear time trend and country dummies. Model 2 is a plot-level model, controlling for inputs, weather, country dummies, and other control variables. Model 3 is analogous to 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 *SI Appendix*, Table S3 for point estimates, sample size, and a full list of variables.

outliers and missing values and varying the composition of crops and of countries in the sample. These additional specifications find either negative or zero productivity growth.* We find no evidence that these trends differ substantially between small and large farms in our sample. We also find no indication that the results are driven by specific crops, nor do they differ when using different sources of weather data. Instead, the negative (or nonpositive) trends recur consistently across many specifications.

Differential Productivity Trends across Countries. There is substantial cross-country heterogeneity in both the levels and trends of productivity. Plots in Nigeria produce higher yields than other countries (*SI Appendix*, Fig. S1), while, over time, we find significant yield declines in Malawi and Nigeria but no significant changes in Ethiopia, Mali, and Tanzania, and positive growth in Niger (Table 1).

We run the baseline model with a full set of plot-level controls for each country separately to estimate TFP (*SI Appendix*, Table S5). We find robustly negative changes in productivity in Nigeria (−4.8%: CI: −6.9% to −2.7%) and Malawi (−3.5%; CI: −4.9% to −2%) and no significant changes in Tanzania (− 0.3%; CI: −2.7% to 2.2%), Ethiopia (0.0%; CI: −2.6% to 2.6%), and Mali (−3.7%; CI: −8.7% to 1.2%). There is an apparent growth spurt, however, in Niger (29%; CI between 23.6% to 34.5%), although 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 baseline model. The cases of Ethiopia, Tanzania, and Mali have relatively large SEs such that modest productivity growth is consistent with our findings.

Discussion

The results of our analysis raise numerous questions and concerns. The low (and possibly negative) rates of productivity growth are discouraging in relation to Africa's progress toward targets 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 of productivity growth from the substantial investments that have been made in the agricultural sector over the past 20 y, including in agricultural research. We do not, of course, have a meaningful counterfactual for comparison; perhaps productivity growth would have been still worse in the absence of these investments—especially given the challenges of climate change and environmental degradation. We also recognize that investments have been highly uneven across Africa (8), with many countries experiencing little or no growth in research expenditure or other sector-specific investments. Another possibility is that time lags may limit our ability to see the impact of past investments. Given the nature of agricultural research, for instance, it is not uncommon to find time lags of 15 or 20 y between research and observed impact. The same may be true for other investments in agriculture, such as those in extension or rural road construction. In that sense, the positive impacts of past investments may not yet have borne fruit.

We also acknowledge that 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 (17, 18). 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.

*Materials and methods are available as supplementary materials.

Table 1. Country-level baseline results

		Ethiopia	Malawi	Mali	Niger	Nigeria	Tanzania
		(1)	(2)	(3)	(4)	(5)	(6)
Model 1: simple time trend	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)
	Sample size	36,195	17,056	30,817	7,029	17,148	7,383
	R-squared	0.000	0.010	0.000	0.120	0.020	0.000
Model 2: baseline plot- level model	Annual time trend	−8.69e-05	−0.0348***	−0.0374	0.290***	−0.0479***	−0.00264
		(0.0131)	(0.00733)	(0.0252)	(0.0274)	(0.0107)	(0.0125)
	Sample size	36,195	17,056	30,817	7,029	17,148	7,383
	R-squared	0.237	0.336	0.470	0.444	0.408	0.379

This table presents regression results (point estimates and SEs 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. The dependent variable is output in constant USD per hectare.

As noted above, our data come from surveys of household farms which omit the commercial farm sector. There is limited evidence at present on the number and size of medium and large farms. We note that the National Sample Census of Agriculture 2019/20 in Tanzania suggests that large- scale farms of 20 ha or larger produced less than 2% of cereals in the preceding rainy season (19). Similarly, in Ethiopia, according to the Large and Medium Scale Commercial Farms Sample Survey of 2020/21, these farms contributed about 5% of total crop production in 2020 (20). If these numbers are taken at face value, then smallholder producers account for very large fractions of output in these two countries, making it implausible that rising productivity on large farms could reverse the trends that we observe in our sample. However, recent research (21–24) suggests that commercialized medium- and large-scale farms are more numerous than previously thought and are growing rapidly in importance. Our sample captures some of these developments (we use the same data as these recent studies), but importantly, it underrepresents medium and large-scale farms (24). Given these recent findings, we emphasize that our results pertain only to the smallholder sector.

Other limitations are also salient. Since we are using panel data (tracking the same households through time), our estimates may miss the contribution of some new farms and younger farmers, whose productivity may differ from existing farms. We can partially address this concern by showing that using cross-sectional data from Malawi covering the same period yields a similar, negative time trend as the panel data (*SI Appendix*, Table S16).

Although our analysis controls for a large and complex set of weather variables, we cannot rule out the possibility that changes in weather or climate may account for the yield declines that we observe—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. However, while our analysis shows that weather variables have a significant impact on productivity levels, we have not identified changes in weather realizations over this period that can account for the productivity changes that we observe over time. Beyond climate change, we note that there are many potential explanations for declining yields and productivity. For instance, yield declines might reflect declining soil fertility; reductions in the quality of land in cultivation; worsening of crop diseases and pest ecology; or perhaps shifts in unmeasured inputs into production (e.g., managerial intensity, worker skills, or seed quality). There is clearly a need for further research to understand the roles played by these or other factors in driving yield and productivity declines.

The results highlight the enormous challenges facing the agricultural science community and the global development community in alleviating poverty in sub-Saharan Africa. Given the observed productivity trends, it will be difficult to meet SDG targets and other stated objectives for policy. The results also point to the need for a careful examination of the factors holding back productivity growth. Agricultural investment strategies must recognize the huge challenges faced by smallholder farmers in Africa. Among these challenges are rapidly evolving disease and pest ecologies, soil degradation, and climate change. The uneven results across countries also suggest that there may be important impacts from policy and national priorities.

Finally, this study also underscores the continuing need for 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.

Materials and Methods

Data and Variables. ***Survey data.*** To undertake this analysis, we harmonized data from longitudinal LSMS-ISA surveys in six countries: Ethiopia, Malawi, Mali, Niger, Nigeria, and Tanzania. Some LSMS-ISA country surveys were excluded because they did not contain a minimum set of control variables for the analysis. The LSMS-ISA surveys use a stratified two-stage sampling procedure, with population and housing census enumeration areas (EAs) as primary sampling units and households as secondary sampling units. Census enumeration areas are selected in the first stage with probability proportional to size and households are randomly selected in the second stage following a household listing in each selected EA.

Most surveys are representative at the national and subnational level (applying the appropriate sampling weights) and are stratified by administrative division and urban/rural levels (exceptions are listed below). For this analysis, only households engaged in crop cultivation were retained. We harmonized the data at the plot level. Only cultivated plots on which seasonal crops are grown were retained in the dataset. Plots with missing harvest values due to, for example, complete crop failure, delayed harvest seasons, nonresponse, or missing unit conversion factors were excluded from the analysis as were those entirely dedicated to growing perennial crops.

Respondents are selected to be knowledgeable of the agricultural activities of their farms, typically plot managers. Informed consent is obtained from each respondent. In case of refusal, a replacement household and respondent are selected. Respondents then provide input and output information on a specific agricultural season. Information from Famine Early Warning System Network (FEWSNET) was integrated into the dataset to determine the timing of the agricultural seasons.

The surveys have a longitudinal structure, whereby households (including split-off households in some countries) and individuals are tracked across waves in five out of six countries (Tanzania, Ethiopia, Malawi, Niger, and Nigeria). Plots or parcels can also be traced in Malawi, Ethiopia, and Tanzania. In Mali, tracking is only possible at the level of the enumeration area (EA). Each country was observed in at least two surveys waves, and each country-wave is associated with a country-specific agricultural production season (*SI Appendix*, Table S1).

For Ethiopia, data from the Ethiopian Social Survey (ESS) were assembled across four survey periods: 2010/2011, 2012/2013, 2014/2015, and 2017/2018. For Malawi, data from the Integrated Household Panel Survey (IHPS) were assembled across four periods: 2009/2010, 2012/2013, 2015/2016, and 2018/2019. For Mali, data from the Enquête Agricole de Conjoncture Intégrée (EACI) were assembled from two periods: 2014 and 2017. For 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. For Nigeria, data were assembled from the General Household Survey (GHS) across four periods: 2010/2011, 2012/2013, 2015/2016, and 2018/2019. Finally, for Tanzania, data were assembled from the National Panel Survey (NPS) across five periods: 2008/2009, 2010/2011, 2012/2013, 2014/2015, and 2018/2019. We also included the cross-sectional Malawi Integrated Household Survey 2010/2011, 2016/2017, and 2019/2020, used in a robustness check reported in *SI Appendix*, Table S16.

Weather data. To account for the impact of weather, we integrated daily temperature data (from the European Centre for Medium-Range Weather Forecasts' ERA5 reanalysis model) and daily precipitation data [Climate Hazards Group InfraRed Precipitation with Station (CHIRPS) data] with the survey dataset based on geolocations recorded in the survey. These recorded geolocations are slightly offset from the true locations, to preserve the anonymity of households and survey villages, so our weather data are adjusted accordingly to account for the offset. From the raw data, we created a large set of weather variables deemed relevant for agriculture in previous studies (25–27).

Variables. The principal outcome variable of interest for our analysis is yield (output value per hectare of land). Because the farms in our sample grow many crops—and frequently grow multiple crops on the same plot—our preferred statistical specifications aggregate crop production at the plot level using a set of price-based weights. Specifically, output is valued with a set of constant prices for each country and then converted to 2020 USD, using CPI and exchange rate data from the World Development Indicators database (28).

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. In addition to output, the following plot-level agricultural inputs variables were prepared for the analysis: land area in hectares, family and exchange labor (i.e., labor exchanged with other households in the community) days per hectare, value of seeds per hectare, value of hired labor per hectare, and value of inorganic fertilizer per hectare. Family and exchange labor days could not be valued because they are not associated with a wage rate, so these were combined and expressed in terms of nonhired labor days per hectare. We similarly use land area rather than the value of land as the value of land could not be estimated reliably because of data limitations on land rental rates. Input and output variables were winsorized at the 99th percentile and log-transformed using the function ln(x+1), for each variable x. We also compute an agricultural assets index by calculating principal component factors, to quantify agricultural asset ownership in a single dimension drawn from an inventory of household assets. To do this, a regression method was used to predict factor scores (29). Finally, we use a continuous and linear year variable to capture the time trend.

The analysis also includes a rich set of plot, household, individual, and geographic control variables. These covariates consist of 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 shocks within the agricultural season (e.g., drought, flood, fire). The age, gender, and formal education status of the plot manager were also included. In addition, a set of household-level controls were included in the model. They comprise a variable for household size, along with dummy variables for recent household shocks (e.g., death of a family member), livestock ownership, household electricity access, and urban/rural status. An indicator equal to 1 if one or more seasonal crops planted on the plot contain missing harvest values was also included.

Estimation Methods. We estimate several statistical models to capture productivity growth. First, we estimate the raw yield time trend in a simple OLS model in which plot-level yields are regressed on an annual time trend and country fixed effects. This specification (also referred to as "model 1" in Fig. 1) can be written as

$$\ln\left(\frac{Y_{it}}{L_{it}}\right) = \alpha + \beta year_t + C_i + \varepsilon_{it}, \quad [\mathbf{1}]$$

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 baseline model (model 2) for estimating agricultural productivity growth for plot i in agricultural season t is the following:

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

where I is a vector of input variables indexed by j (where $j = 1,\ldots, J$) and X a vector of household and plot controls indexed by l (where $l = 1,\ldots, K$). The agricultural assets index and log-transformed plot area variables were 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 chosen by a LASSO algorithm. The term M_{it} denotes main crop dummies. 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} is a residual. To the extent that Eq. **2** is well specified, β captures the linear yearly growth component of TFP. Since households can be tracked in most of the sample, data were aggregated at the household level such that for each household h, agricultural productivity was estimated in the following form (model 3):

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

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

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

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):

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

Mali is excluded from the analysis for models 4 and 5, as households and farmers cannot be tracked. In addition, the following cluster-level fixed effects model is specified (model 6):

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

Finally, we revalue inputs and outputs using time- and region-specific current prices, rather than constant prices (model 7). We run all regressions both on the full cross-country sample and for each country separately.

SEs are clustered at the enumeration area (EA) level, accounting for correlated shocks. SEs also take into account the surveys' sampling designs, using a Taylor linearization method. While SEs are linearized in most specifications, they are bootstrapped in fixed effects models (30, 31).

All specifications are implemented with population weights which reflect the approximate population size each data point represents and account for the multistage sampling design of each country and wave. The sampling weights are adjusted to correct for attrition and scaled up to reflect the omission of nonagricultural households (*SI Appendix*, section 1.B).

Data, Materials, and Software Availability. Anonymized Stata format microdata have been deposited in Zenodo (https://doi.org/10.5281/zenodo.6977263).

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