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Mismeasurement and Efficiency Estimates

Evidence from Smallholder Survey Data in Africa

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Abstract

Smallholder agriculture in sub-Saharan Africa is commonly characterized by high levels of technical inefficiency. However, much of this characterization relies on self-reported input and production data, which are prone to systematic measurement error. We theoretically show that non-classical measurement error introduces multiple identification challenges and sources of bias in estimating smallholders' technical inefficiency. We then empirically examine the implications of measurement error for the estimation of technical inefficiency using smallholder farm survey data from Ethiopia, Malawi, Nigeria, and Tanzania. We find that measurement error in agricultural input and production data leads to a substantial upward bias in technical inefficiency estimates (by up to 85 percent for some farmers). Our results suggest that existing estimates of technical efficiency in sub-Saharan Africa may be severe underestimates of smallholders' actual efficiency and what is commonly attributed to farmer inefficiency may be an artifact of mismeasurement in agricultural data. Our results raise questions about the received wisdom on African smallholders' production efficiency and prior estimates of the productivity of agricultural inputs. Improving the measurement of agricultural data can improve our understanding of smallholders' production efficiencies and improve the targeting of productivity-enhancing technologies.

Keywords: measurement error, technical efficiency, misreporting, plot size, smallholder farming, survey data, DNA fingerprinting, crop cuts.

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1. Introduction

Mainstream development economics has generally maintained the assumption that smallholder farmers are rational agents who aim to maximize farm profits by choosing the optimal level and mix of agricultural inputs (Schultz, 1964). However, several empirical studies in developing countries have shown that input use levels, as well as smallholder production outcomes, are inconsistent with Schultz's hypothesis that farmers are "poor but efficient" (Sherlund et al., 2002; Duflo, 2006; Duflo et al., 2011). More specifically, smallholder agriculture in sub-Saharan Africa is frequently characterized by two important empirical patterns which are not consistent with this neoclassical theory. First, the low level of adoption of seemingly profitable agricultural technologies in many African countries is inconsistent with this argument.[1] Second, a large number of empirical studies document pervasive technical inefficiency (e.g., Sherlund et al., 2002; Berkhout et al., 2010; Bravo-Ureta et al., 2007; Coelli and Fleming, 2004; Karagiannis and Sarris, 2005) as well as allocative inefficiency (e.g., Restuccia and Santaeulalia-Llopis, 2017; Gollin and Udry, 2021) in African agriculture.[2] Such production inefficiencies have been frequently invoked to justify public investments aimed at improving production efficiency in smallholder farming systems.

It is possible that many of these empirical conclusions and assertions about farmer inefficiencies are simply statistical artifacts driven by mismeasurements in agricultural data. The estimation of technical inefficiency has typically relied on self-reported and recall-based agricultural data – including input quantity, type and quality, and production data – which are now known to suffer from systematic misreporting (Carletto et al., 2013; Carletto et al., 2015; Desiere and Jolliffe, 2018; Gourlay et al., 2019; Abay et al., 2019; Kosmowski et al., 2021) as well as misperceptions in subjective reports (Ashour et al., 2019; Michelson et al., 2021; Wineman et al.,

[1] There exist several explanations justifying the low adoption of improved technologies in African agriculture. One strand of economic literature attributes this to input market imperfections (e.g., Duflo et al., 2011; Minten et al., 2013), while another branch of the literature attributes this to the low, uncertain and/or variable profitability of modern inputs for African smallholders (e.g., Duflo et al., 2008; Marenya and Barrett, 2009; Suri, 2011; Burke et al., 2017; Liverpool-Tasie et al., 2017; Abay et al., 2018; Michler et al., 2019).

[2] Technical efficiency is the effectiveness with which a given set of inputs is used to produce an output. Allocative efficiency occurs where the price of an output equals its marginal cost of production. Allocative inefficiency in agricultural production may occur when land and/or capital is not optimally allocated with respect to farmer skill.

2020; Abay et al., 2021; Burke et al., 2020; Wossen et al., 2021).[3] Despite some recent attempts to examine the inferential implications of measurement error in agricultural data, no prior study has explored its implications for the estimation of technical inefficiency. We address this gap with the present study.

Using recent farm survey data from Ethiopia, Malawi, Nigeria and Tanzania, we evaluate the sensitivity of technical inefficiency estimates to measurement error in (i) plot size, (ii) production (output) amount, and (iii) crop variety. We particularly evaluate six cases of mismeasurement involving these countries and agricultural metrics. To guide our analyses, we consider a simple analytical framework involving two-sided measurement error in a stochastic production frontier model. We find that measurement error in agricultural input and production data leads to a substantial upward bias in technical inefficiency estimates. Our empirical results suggest that prior assessments of smallholders' technical efficiency which have relied on standard self-reported farm survey data are likely to be severe underestimates of actual efficiency levels. Our findings are consistent with recent evidence showing that measurement error can confound estimation of production inefficiencies. For example, Gollin and Udry (2021) find that measurement error inflates estimates of smallholders' allocative inefficiency, and Abay (2020) finds that marginal returns to factors of production are inflated by self-reported measures.[4] Our results underscore the potential costs of inaccuracies in agricultural data and agricultural input market imperfections in sub-Saharan Africa. Addressing these data limitations can improve our understanding of smallholders' production efficiency and its drivers, and as a result may help clarify what policy and investment options are most conducive for raising productivity.

The remainder of the paper is structured as follows: Section 2 introduces an analytical framework relating measurement error with technical inefficiency. Section 3 and 4 presents the data and the empirical strategy, respectively. Section 5 reports the main results, and section 6 offers concluding remarks.

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[3] Misreporting stands for erroneously reporting or recording of survey data, while misperception represents the deviation between subjective assessments of surveyed values and the true values. For example, an error arising from rounding values is a typical example of misreporting which may distort inferences while misperceptions about the quality of inputs may affect both farmers' input use decisions as well as researchers' inferences.

[4] Our findings are also consistent with some empirical studies showing that endogeneity and omitted variables in stochastic production frontier models lead to overestimation of technical inefficiency (Sherlund et al., 2002; Shee and Stefanou, 2015).

2. Analytical Framework: Measurement Error and Technical Inefficiency

In this section, we lay out a simple analytical framework to examine the implications of measurement error in agricultural data for estimation of technical inefficiency. For convenience, we first define a log-transformed maximum attainable production frontier (Y_{it}^{f}), log-transformed realized production (Y_{it}^{*}), a log-transformed agricultural input (X_{it}^{*}) and a positively valued measure of technical inefficiency ($u_{it}^{*} \geq 0$). Following the literature on technical efficiency analysis (e.g., Sherlund et al., 2002; Wang and Schmidt, 2002; Greene, 2005; Chen et al., 2014; Kumbhakar et al., 2015; Belotti and Ilardi, 2018; Kutlu et al., 2019), the relationship between realized production and an agricultural input can be expressed using the following stochastic production frontier function:[5]

$$Y_{it}^{*} = Y_{it}^{f} - u_{it} = X_{it}^{*}\beta + [v_{it} - u_{it}] = X_{it}^{*}\beta + \epsilon_{it} \qquad (1)$$

where Y_{it}^{*} stands for realized (log-transformed) production for a farmer i at a specific time t, β represents a technology parameter, which can also be interpreted as an output elasticity for those specifications involving log-transformed production and inputs. ϵ_{it} is a composite error term containing the usual two-sided symmetric idiosyncratic error (v_{it}) and a one-sided strictly positive inefficiency term (u_{it}) (i.e., $\epsilon_{it} = v_{it} - u_{it}$).[6] We note that the above simple bivariate relationship between an agricultural input and output is not realistic (and hence will be relaxed in our empirical estimations) as agricultural production usually involves multiple inputs. However, such simplification helps to avoid mismeasurements in multiple variables as well as the implication of mismeasurement in one agricultural input on parameter estimates associated with other agricultural inputs. We also note that technical inefficiency in this formulation is time-varying. Smallholders' production efficiency could vary across years because of peculiar production shocks or change in managerial skills. However, some components of inefficiency may effectively be time-invariant, an empirical question we address in Section 5.

Empirical identification and estimation of technical inefficiency involves some important steps and assumptions. First, estimation of the technical inefficiency term requires recovering the

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[5] We use the terms "output" and "production" synonymously in this paper.

[6] If both the maximum attainable production and actually observed production are log-transformed, a farmer's technical inefficiency, $u_{it} = Y_{it}^{f} - Y_{it}^{*}$, can be interpreted as percentage deviation of a farmer's actual production from his/her own frontier.

technology parameter (β) and prediction of the composite error term using these parameters. Recovering the technology parameter (β) from equation (1) and the composite error in equation (1) requires the assumption that agricultural input application X_{it}^* is independent of the composite error and hence technical inefficiency, an assumption that corresponds to exogeneity of input choice. Second, disentangling the technical inefficiency (u_{it}) and the idiosyncratic error term (v_{it}) requires further distributional assumptions about u_{it} and v_{it}. For this purpose, u_{it} is commonly assumed to follow a truncated normal distribution, $u_{it} \sim N^+(\mu, \sigma_u^2)$, while v_{it} is usually assumed to follow a symmetrical normal distribution, $v_{it} \sim N(0, \sigma_v^2)$. u_{it} and v_{it} are also assumed to be uncorrelated ($cov(u_{it},\ v_{it}) = 0$)). With these distributional assumptions and when inputs are correctly measured and farmers have perfect information about their inputs, consistent estimates of technology parameters can be recovered using maximum likelihood estimation (MLE). Using these distributional assumptions, there exist well-defined methods for identifying and recovering the technical inefficiency term (u_{it}) from the composite error in equation (1) (e.g., Jondrow et al., 1982; Battese and Coelli, 1988; Kumbhakar and Lovell, 2000).[7]

The presence of measurement error in agricultural data and imperfect information about input quantity or quality may confound estimation of technical inefficiency. There are several channels through which measurement error in input and production data can affect statistical inference related to technical inefficiency. To illustrate these implications, let us consider that measurement error in agricultural data represent simple misreporting, erroneous reporting or recording of survey data. For convenience, let us assume that both input and production can be measured with error. That is, instead of true measures of input (X_{it}^*) and output (Y_{it}^*), we observe error-ridden self-reported measures, X_{it} and Y_{it}, respectively. Assuming that measurement error enters additively, the relationship between the true and the mis-measured values can be expressed as follows:

[7] The most common decomposition, known as JLMS (Jondrow et al., 1982; Greene, 2005) uses the following expression to extract technical inefficiency, $E[u_{it}|\epsilon_{it}] = \frac{\sigma\xi}{1+\xi^2}[\frac{\phi(-\epsilon_{it}\,\xi/\sigma)}{1-\Phi(-\epsilon_{it}\,\xi/\sigma)} + \epsilon_{it}\,\xi/\sigma]$, where, $\sigma = [\sigma_v^2 + \sigma_u^2)/2$, $\xi = \frac{\sigma_u}{\sigma_v}$, and $\phi(.)$ and $\Phi(.)$ denote the standard normal density and CDF functions, respectively. We note that the ability to decompose the composite error into an inefficiency term (u_{it}) and an idiosyncratic term (v_{it}) heavily relies on the distributional assumption that the former is one-sided while the latter is symmetrically distributed and mean zero. This is equivalent to attributing skewness of the distribution of the composite term to the inefficiency term. Potential failure in these assumptions will confound identification and disentangling of these terms.

$$Y_{it} = Y_{it}^* + \omega_{it}$$
$$X_{it} = X_{it}^* + \lambda_{it} \qquad (2)$$

For simplicity, we assume that measurement error in input (λ_{it}) and production (ω_{it}) is independent within panel observations (e.g., plot observations at different points in time) and uncorrelated to each other. Measurement error can behave classically or non-classically.[8] In this context and in the absence of objective measures of agricultural inputs and production, researchers usually estimate technology parameters and technical inefficiency estimates using self-reported values. By substituting the expressions in equation (2) into equation (1) the original stochastic production function becomes:

$$Y_{it} = X_{it}\beta + [v_{it} + \omega_{it} - \lambda_{it}\beta - u_{it}] = X_{it}\beta + [\tilde{v}_{it} - u_{it}] = X_{it}\beta + \tilde{\epsilon}_{it} \qquad (3)$$

There are at least two identification challenges in estimating technical inefficiency using the expression in equation (3). First, the technological parameter estimate in equation (3) will be inconsistent because λ_{it} is correlated with X_{it}.[9] The bias in this estimate will depend on the nature of measurement error: whether measurement error behaves classically or non-classically. Second, measurement error in production ω_{it} adds further complications in identifying the technological parameter in equation (3). While classical measurement error in production is not expected to affect estimates of technology parameters (i.e., output elasticities), recent studies have documented non-classical measurement error in agricultural production data (e.g., Desiere and Jolliffe, 2018; Gourlay et al., 2019; Abay et al., 2019; Abay, 2020). These studies show that measurement error in crop production is negatively correlated with true production and true land area, implying that smaller harvests (plots) are overestimated while larger harvests (plots) are underestimated. Ultimately these inconsistencies in technological parameters can confound identification and estimation of technical inefficiency estimates.

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[8] Nonclassical measurement error occurs when the error in a variable of interest is correlated with the true value of that variable or with other variables in the model (Bound et al., 2001). Classical error, in contrast, is random.
[9] Implicitly, the composite error in equation (3) is now correlated with X_{it} because λ_{it} remains part of the new composite error $\tilde{\epsilon}_{it}$.

Overall, the above exposition implies that measurement error introduces multifaceted sources of bias in stochastic frontier production function estimation and hence tackling measurement error in these models is much more difficult than in a traditional linear regression setup where the focus is on identifying technology parameters as average partial effects. One may impose some simplifying assumptions (on the nature of production function and measurement error) to gauge the direction of bias in technical inefficiency estimates due to mismeasurement in input or production data. For example, let us consider that the production function in equation (1) is deterministic ($Y_{it}^* = Y_{it}^f - u_{it} = X_{it}^*\beta + u_{it}$). In this case, an ordinary least square (OLS) estimation of equation (2) with classical measurement error in an explanatory variable (agricultural input) will lead to an attenuation bias in technological parameter, which ultimately leads to an upward bias in expected (average) technical inefficiency.[10]

3. Data

We consider mismeasurement in three types of input and output data: (i) plot size, (ii) crop variety type, and (iii) crop harvest, all of which have been shown to be prone to measurement error (e.g., Carletto et al., 2013; 2015; Desiere and Jolliffe, 2018; Gourlay et al., 2019; Abay et al., 2019; Kosmowski et al., 2019; Kosmowski et al., 2021; Wossen et al., 2019a; Wossen et al., 2019b). Although some of these studies have considered the implications of mismeasurement for productivity analysis (e.g., the inverse size-productivity relationship), there has been no prior study of the implications of such mismeasurement for the estimation of technical inefficiency, an important target of agricultural policy. In this paper we evaluate the sensitivity of technical inefficiency estimates to potential mismeasurements in agricultural input and output data. For this purpose, we use data from multiple sources: (i) the Living Standard Measurement Study-Integrated Surveys on Agriculture (LSMS-ISA), and (ii) the Cassava Monitoring Survey (CMS) from

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[10] This can be shown by comparing the expected technical inefficiencies associated with deterministic versions of equation (1) and (2). Let us assume that inputs are production-enhancing and let $\hat{\beta}$ and $\tilde{\beta}$ be the OLS estimates from deterministic production functions associated with equation (1) and (2), respectively. Similarly, let $\hat{u}_{it}$ and $\tilde{u}_{it}$ be the corresponding technical inefficiency estimates associated with equation (1) and (2), respectively. In the presence of classical measurement error $\tilde{\beta} < \hat{\beta}$ due to attenuation bias. Thus, $E(\tilde{u}_{it}) - E(\hat{u}_{it}) = (\hat{\beta} - \tilde{\beta})E(X_{it}^*) > 0$.

Nigeria. These data sources provide both self-reported and objective measures of inputs and production for several countries, allowing us to evaluate six cases of mismeasurement (Table 1).

Table 1: Case studies evaluated

Country	Source of measurement error: Land area (continuous)	Production (continuous)	Variety (categorical)	Data source
Ethiopia	X	X		LSMS-ISA
Malawi	X			LSMS-ISA
Nigeria	X		X	CMS
Tanzania	X			LSMS-ISA

Notes: CMS = Cassava Monitoring Survey. LSMS-ISA = Living Standards Measurement Survey – Integrated Survey of Agriculture.

3.1. Land area and production measurement

For our examination of mismeasurement in land area and production, we employ LSMS-ISA data for Ethiopia, Malawi and Tanzania, along with comparable data from the CMS from Nigeria. The LSMS-ISA data are collected by national statistical offices of countries in collaboration with the World Bank. These data are nationally representative and provide comparable information on agriculture across countries. The Ethiopian LSMS-ISA data include three rounds of panel data, collected in 2011/12, 2013/14, and 2015/16. For Malawi, we use three rounds of the LSMS-ISA data, collected in 2010/11, 2013, and 2016/17. For Tanzania, we also use three rounds of data from the LSMS-ISA: 2008/9, 2010/11, 2012/13. A key feature of these data is the collection of both self-reported and objective measures of many variables, including land area and production. Land area measurements are conducted at plot level, with plot sizes first elicited from farmers self-reporting and then measured using GPS receivers.[11]

Additionally, for Ethiopia, we examine data on crop production as measured by farmer self-reporting as well as through crop-cuts. The crop-cutting exercise involves selection of one random subplot (2 meters × 2 meters or 4 meters × 4 meters), which is then harvested, and the resulting crop output weighed.[12] We then extrapolate this harvest from a random subplot to compute the overall plot-level production. Due to the expensive nature of crop-cutting exercises,

[11] A key assumption here is that GPS measures are more accurate and closer to the true values than farmer-reported measures. This is supported by recent empirical work (Carletto et al., 2017).

[12] The size of subplots chosen for crop-cutting vary across rounds.

crop cuts were administered for five randomly selected plots per crop in each enumeration area.[13] As a result, our investigation of the impact of measurement error in crop production is based on the sub-sample of about 7300 plots in which crop-cuts were administered.

Table 2 presents summary statistics of households and plots, including all household and plot-level controls used in our estimation. The mean differences between self-reported and objective measures of plot size and production in Table 2 are modest, although what matters most for inference is the distribution of these differences, particularly with respect to the distribution of true plot size and production, as well as across other observable characteristics of households and plots. Figure 1 clearly shows that, for most countries, self-reported plot size exhibits strong bunching around some integers and simple fractions (e.g., 0.5, 1, 1.5, 2, 2.5 acres). Such bunching is not visible in the Ethiopian data, implying that the sources of measurement error in land area measurement could vary across countries.[14]

[13] Detailed instructions and manual for crop-cutting exercises can be found at http://go.worldbank.org/ZK2ZDZYDD0

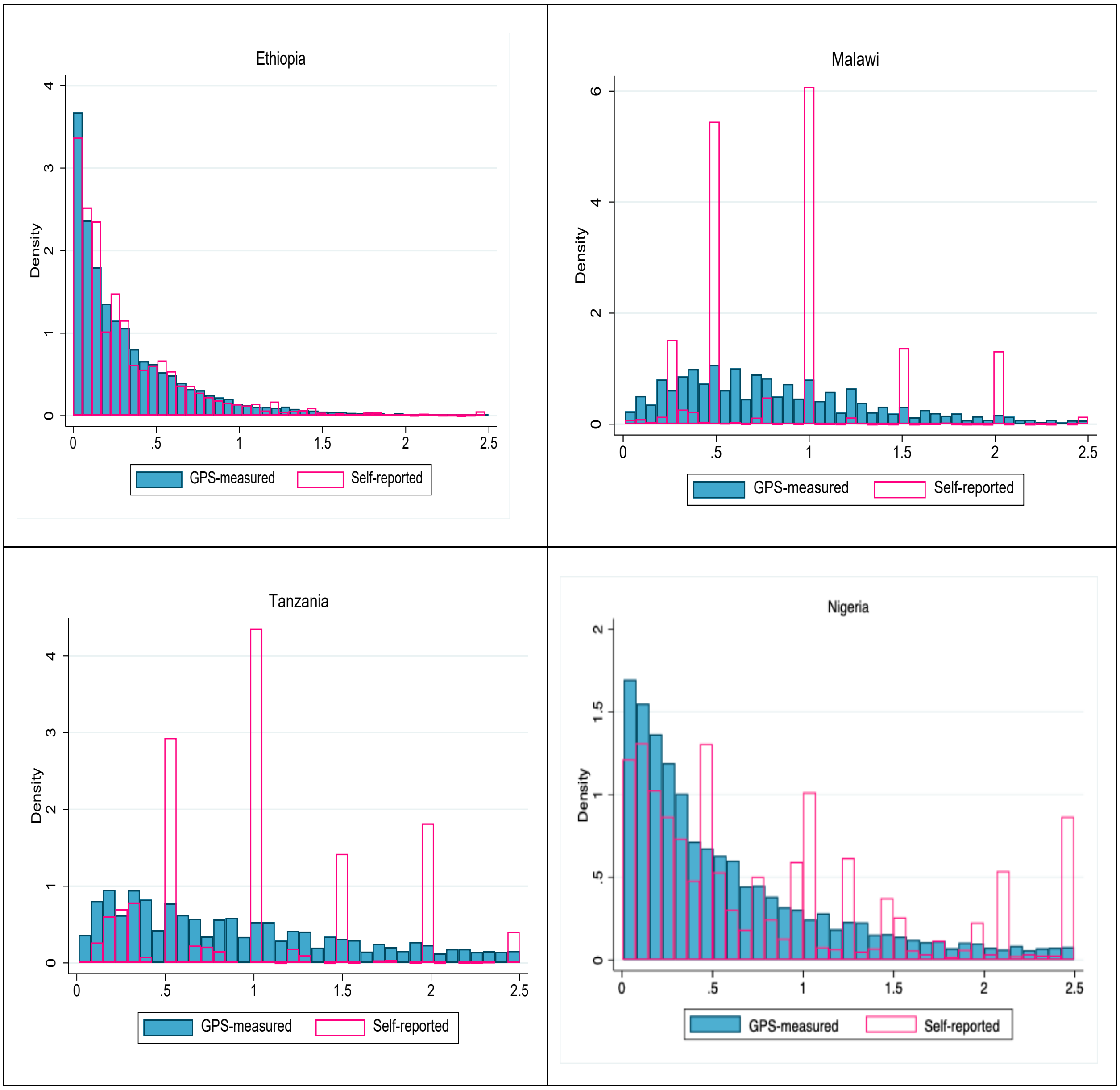
[14] Some of these differences may be driven by unit of measurement. In Ethiopia farmers usually measure land area using *oxen days* than acres, although we fail to observe major bunching of plot sizes when using *oxen days*.

Table 2: Pooled summary statistics of households and plots

Variable of interest	Ethiopia	Malawi	Nigeria	Tanzania
Land area and production measurement				
Plot size: Self-reported (acre)	0.35(0.43)	0.96(0.75)	1.28(1.97)	2.73(6.19)
Plot size: GPS (acre)	0.37(0.46)	0.94(0.82)	0.89(1.26)	3.08(7.41)
Farm size: GPS (acre)	3.57(3.43)	3.01(4.17)		8.14(15.85)
Production (kg)-self-reported	156.49(389.51)	577.7(2098.1)	3859(8972)	2098.2(88028.8)
Production (kg)-self-reported [a]	148.04(277.86)			
Production (kg)-crop-cut [a]	237.26(255.36)			
Household characteristics:				
Gender household head (1=male)	0.83(0.37)	0.76(0.43)	0.89(0.31)	0.78(0.42)
Age of household head (years)	48.16(14.21)	44.04(16.12)	52(13.5)	49.6(15.88)
Household-head literate (1=yes)	0.42(0.49)	0.14(0.34)	0.89(0.32)	0.72(0.45)
Household size (persons)	5.66(2.23)	4.9(2.22)	4.5(2.3)	5.97(3.56)
Acres per person (acres/persons)	0.7(0.81)	0.74(1.09)		1.47(2.64)
Plot characteristics				
Irrigated plot (1=yes)	0.04(0.19)	0.01(0.07)		0.02(0.15)
Soil quality perceived as good (1=yes)	0.31(0.46)	0.48(0.5)	0.73(0.44)	0.47(0.50)
Plot managed by men (1=yes)			0.37(0.48)	
Plot managed jointly (1=yes)			0.47(0.50)	
Steep slope (1=yes)	0.11(0.32)	0.43(0.49)		0.31(0.46)
Pure stand cropping	0.76(0.43)	0.54(0.50)	0.88(0.33)	0.84(0.36)
Input use				
Labor days (days)	10.35(15.09)	88.90(55.91)	69.7(67.4)	75.55(74.3)
Fertilizer (1=yes)	0.28(0.45)	0.58(0.49)	0.34(0.47)	0.15(0.35)
Pesticides/herbicides (1=yes)	0.13(0.33)	0.02(0.13)	0.45(0.49)	0.02(0.13)
Improved cassava variety: self-reported (1=yes)	0.35(0.48)	0.69(0.46)	0.52(0.50)	0.22(0.41)
Improved cassava variety: DNA (1=yes)			0.67(0.47)	
False positive (1=yes) [b]			0.33(0.47)	
False negative (1=yes) [b]			0.39(0.49)	
Number of observations	28,934	30,808	4,122	7,260

Notes: except for plot size and production measures, the remaining information for the above variables are self-reported by farmers during the household surveys. Values outside parenthesis provide mean values while those inside parentheses are standard deviations. [a] Small sample stands for the sample of plots administered for crop-cutting exercise. [b] For the crop variety data, we define false positive as: (Self-reported=1|DNA=0) and false negative as: (Self-reported=0|DNA=1).

Figure 1: Distribution of self-reported and GPS plot sizes



Notes: Values on the x-axis indicate plot area measurements in acres.

We define measurement error as log-transformed differences between self-reported and objective (i.e., GPS- and crop-cut-derived) measures with the intention of constructing an indicator of measurement error relative to true measures. Table 3 provides a saturated parametric characterization of these errors, while Figure A1 (in the Appendix) provides a nonparametric characterization of measurement error as a function of true values of measures. These results show an inverse relationship between measurement error in plot size and true plot size – i.e., larger plots are underestimated in self-reported land area measurement, while smaller plots are overestimated – suggesting that measurement error in self-reported plot size behaves non-classically for all countries. Comparing self-reported and crop-cut measures of production (column 5 of Table 3) indicates a similar relationship. These results are consistent with previous findings that farmers generally over-estimate smaller plots and harvests, and under-estimate larger plots and harvests (Carletto et al., 2013; 2015; Desiere and Joliffe, 2018; Abay et al., 2019; Gourlay et al., 2020). The magnitudes of these mean-reverting relationships suggest that measurement error is reasonably large and potentially consequential.

Table 3: Characterizing measurement error in self-reported land area and production

Explanatory variables	(1) Ethiopia (land area)	(2) Malawi (land area)	(3) Nigeria (land area)	(4) Tanzania (land area)	(5) Ethiopia (production)
ln (plot size: GPS)	-0.303***	-0.480***	-0.776***	-0.397***	
	(0.009)	(0.009)	(0.026)	(0.14)	
ln (production: crop-cut)					-0.387***
					(0.015)
Year (time dummies)	Yes	Yes	No	Yes	Yes
Household characteristics	Yes	Yes	Yes	Yes	Yes
Household fixed effects	Yes	Yes	Yes	Yes	Yes
R-squared	0.258	0.368	0.462	0.362	0.220
Number of observations	28,934	30,788	4,122	7,255	7318

Notes: The dependent variables in this table are measurement error in self-reported plot size and production. We define measurement error in relative terms as log(self-reported measure)-log(objective measure). Column 1-4 characterize measurement error in self-reported plot size. Column 5 characterizes measurement error in self-reported production. Standard errors are clustered at household level and given in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

We note that one can still argue that the objective measures of plot size and production may not be free from error. For instance, GPS devices may suffer from potential inaccuracies arising from quality of satellites and receivers (Keita and Carfagna, 2009; Carletto et al., 2017). However, previous evaluations of these measurements show encouraging evidence. Although limited errors associated with GPS devices may not be ruled out, these inaccuracies are found to be less systematic relative to self-reported measures (Carletto et al., 2017). Similarly, although crop-cutting is widely accepted as a reliable method for accurately estimating crop production (Fermont and Benson, 2011)[15], the choice or location of subplots and extrapolation of subplot production may introduce some errors, especially in the presence of significant internal heterogeneity in productivity within plots (Bevis and Barrett, 2020).

3.2. Crop variety identification

For examining the implications of crop variety misclassification, we use variety identification data from the Cassava Monitoring Survey (CMS) in Nigeria. The CMS collected information about the type of cassava varieties grown by farmers using two different approaches. The first is by asking farmers to report the type of cassava variety they grow, specifically whether the cassava variety they grow is improved or not. This corresponds to the standard variety data collection approach often employed in household surveys. Second, leaf samples from all identified cassava plots of farmers were also collected to accurately identify the improvement status of the cassava varieties grown by farmers through DNA-fingerprinting analysis. Since DNA-fingerprinting is independent of environmental conditions or plant growth stage, the type and improvement status of the cassava varieties grown by farmers can be identified accurately (Rabbi et al., 2015). Therefore, the DNA-fingerprinting results can serve as an objective measure of variety type and improvement status.[16]

As shown in Table 2, based on self-reported information, about half of the cassava plots in the Nigeria data are planted with an improved variety while the corresponding rate based on the results of the DNA-fingerprinting analysis is 67%. From the matched plot-level variety data, we find significant mismatches in farmers' self-reported variety information and the results of the the DNA-fingerprinting analysis. More specifically, of the plots reported to be planted with improved varieties, the results of the DNA-fingerprinting indicate that the actual variety is unimproved in 33% of the plots (the false positive rate). Similarly, of the plots reported to be planted with

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[15] Although choice of crop cut methods do matter; see Kosmowski et al. (2021) for a recent comparison of methods in Ethiopian maize fields.
[16] Information about the DNA-fingerprinting process can be accessed at https://cgspace.cgiar.org/handle/10568/80560

unimproved varieties, the results of the DNA-fingerprinting indicate that the planted variety is improved in 39% of the plots (the false negative rate). Unlike plot size and output data, which are typically continuous, variety misclassification cannot be classical since variety type is a binary indicator. Hence, variety misclassification is inherently non-classical as the correlation between the true value and its measurement error is always negative, making the classical measurement error assumptions implausible.[17]

4. Estimation Strategy

Following the analytical framework introduced in Section 2 and the notion that agricultural production is subject to random shocks, such as those associated with weather, disease and pests, we treat agricultural production as a stochastic outcome. We specify the following estimable stochastic frontier model, where a farmer (i) produces output, Y_{itp}^{*} at plot (p) in year (t), using agricultural inputs, X_{itp}^{*} and Z_{itp}^{*}, and technical inefficiency u_{it}≥0**.** For now, we assume that farmers' managerial and technical efficiency varies across years but remains constant across plots in each round (an assumption we probe further in our robustness exercises).[18] Assuming linear relationships between inputs and output, the following specification captures the relationship between correctly measured agricultural inputs and production:

$$Y_{itp}^{*} = \alpha + X_{itp}^{*}\beta + \theta' Z_{itp}^{*} + \left[v_{itp} - u_{it}\right] \tag{4}$$

where v_{itp} is an idiosyncratic error term assumed to be independently and identically distributed, u_{it} is technical inefficiency, and α is a constant term. Estimating the conditional regression (by including additional inputs Z_{itp}^{*}) in equation (4) can improve the plausibility of the assumption that the composite error in equation (4) is uncorrelated with agricultural inputs, although we still doubt this strong assumption holds and hence refrain from claims of strong causal inference.

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[17] That is, in this binary indicator context, the only way to misclassify a true value of one (i.e., an indicator of improved status) is as a zero (i.e., unimproved), while the only way to misclassify a true zero is as a one.

[18] To probe the robustness of our results, we estimate both time-invariant and time-variant technical inefficiency measures. However, this is only possible for Ethiopia, Malawi and Tanzania, where we observe both time and plot-level variation. The Nigeria data only allow examination of plot-level variation because we lack time-variation.

Empirically, disentangling u_{it} and v_{itp} requires further distributional assumptions and decomposition techniques. We assume that v_{itp} and u_{it} follow symmetrically normal and truncated normal distributions, respectively.

However, in the presence of measurement error, one can only observe mismeasured agricultural inputs, $X_{itp} = X^*_{itp} + \lambda_{itp}$, and potentially mismeasured harvest, $Y_{itp} = Y^*_{itp} + \omega_{itp}$. Under this scenario, most researchers instead estimate the following empirical relationship using self-reported agricultural data:

$$Y_{itp} = \tilde{\alpha} + X_{itp}\tilde{\beta} + \tilde{\theta}' Z^*_{itp} + \tilde{v}_{itp} - \tilde{u}_{it} \tag{5}$$

As shown in Section 2, in the presence of measurement error in agricultural inputs and/or output, the inefficiency estimate ($\tilde{u}_{it}$) in equation (5) is an inconsistent estimate of farmers' true inefficiency (u_{it}).

5. Estimation Results and Discussion

5.1 Mismeasurement in land area

In this section, we report results from our analysis of the implications of measurement error in plot size on technical efficiency estimates. For this analysis, we assume that production and other inputs except plot size are measured without error, an assumption that we partially relax in Sections 5.2 and 5.3. Following our empirical strategy, we estimate saturated conditional production functions considering self-reported and objectively measured plot size. Table 4 provides stochastic production function parameters, estimated using maximum likelihood estimation. As both land area and output data are log-transformed, the estimates in Table 4 can be interpreted as elasticities, i.e., percentage changes in production associated with one percent increase in plot size. Each panel provides output elasticities for each country using alternative measures of plot size reported in different columns. All these estimations control for those household and plot-level characteristics and agricultural inputs listed in Table 2, as well as year and crop fixed effects.[19] The first column is based on self-reported plot size while the second column uses GPS-based measurements. Assuming that GPS-based measures capture true plot size and farmers have perfect information

[19] Full results are provided in Tables A1-A4 in the Appendix.

about their inputs (no misperception), the results in the second column can serve as benchmark estimates.

Although the elasticities in Table 4 are not sufficiently informative about the implication of mismeasurement in agricultural inputs in estimating technical inefficiency, we can clearly observe that output elasticities significantly vary across land area measurement methods and specifications. The log-likelihood values increase as we depart from using self-reported plot size, underscoring the notion that actual production responds more to objective plot size than to self-reported area. For all countries, likelihood-ratio tests comparing the log-likelihood values in columns 1 and 2 indicate significant differences in model fit and estimates.

Table 4: Stochastic production frontier estimates using alternative measures of plot size

Explanatory variables	(1) Self-reported	(2) GPS
Panel A: Ethiopia		
Log (plot size: SR)	0.456***	
	(0.006)	
Log (plot size: GPS)		0.509***
		(0.006)
Log-likelihood value	-39764.4	-38688.2
No. observations	26890	26890
Panel B: Malawi		
Log (plot size: SR)	0.543***	
	(0.011)	
Log (plot size: GPS)		0.527***
		(0.009)
Log-likelihood value	-49640.4	-49224.5
No. observations	30785	30785
Panel C: Nigeria		
Log (plot size: SR)	0.374***	
	(0.019)	
Log (plot size: GPS)		0.652***
		(0.016)
Log-likelihood value	-5918.8	-5458.3
No. observations	4122	4122
Panel D: Tanzania		
Log (plot size: SR)	0.463***	
	(0.014)	
Log (plot size: GPS)		0.396***
		(0.012)
Log-likelihood value	-10132.0	-10083.2
No. observations	7255	7255
Year dummies	Yes	Yes
Other inputs	Yes	Yes
Household-level characteristics	Yes	Yes
Plot-level characteristics	Yes	Yes
Crop dummies	Yes	Yes

Notes. The dependent variable in this table is log-transformed production (measured in kg). SR stands for self-reported plot size; GPS represents plot size measured using handheld GPS devices. All regressions control for those household and plot-level characteristics listed in Table 2 as well as year and crop fixed effects. The Nigerian data are only for cassava and controls for DNA-based crop variety instead of self-reported variety. Standard errors are given in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

We next compute farmers' technical inefficiency considering alternative assumptions about the nature of farmers' production efficiency. Using the technological parameters in Table 4 we compute and report technical inefficiencies in Table 5. To uncover potential systematic differences across the distribution of actual (benchmark) technical inefficiencies, we report mean and median values as well as the bottom quintile and top quintile averages computed using alternative measures of land area.[20] These values are computed assuming time-variant (but plot-invariant) technical inefficiency, while similar technical inefficiency values assuming time-invariant technical inefficiency are reported in Table A5 in the Appendix. These values can be interpreted as percentage deviation of farmers' actual production from their own frontier or the potential loss of output due to farm-specific technical inefficiencies. For instance, the first column for Ethiopia shows that an average farmer is producing at the 50th percentile below the frontier (or, equivalently, the average output loss due to technical inefficiency amounts to 50 percent).

Comparing the mean technical inefficiency estimates in column 1 and those in columns 2 of Table 5, suggests that using self-reported plot size leads to significant overestimation of smallholders' average technical inefficiency. For instance, using self-reported plot size inflates smallholders' average inefficiency by about 17-25 percentage points in Ethiopia and Nigeria. Similarly, using self-reported plot size inflates median technical inefficiency by comparable rates. These comparisons suggest that the inaccuracies in land area measurement contribute to substantially lower estimates of technical efficiency than would be the case without measurement error.

Most importantly, the bottom and top quintile values reported in Table 5 show important differences worth highlighting. For instance, in Ethiopia and Nigeria, using self-reported plot size overestimates technical inefficiency of the least inefficient farmers by 37-53 percent while corresponding overestimation rates for the top quintile farmers (most inefficient) farmers amount 6-9 percent. Conversely, self-reported land area measurement leads to underestimation of technical efficiency of the least efficient smallholders. This implies that the implication of measurement error in agricultural inputs are likely to have relatively higher distortionary inferential impacts on the least inefficient farmers.

Measurement error can also distort the whole distribution of technical inefficiency estimates, shifting both the location and scale parameters defining farmers' technical efficiency. In the interest of examining the whole distribution of technical inefficiency estimates, Figure 2 provides kernel density of predicted technical inefficiency levels estimated assuming time-varying

[20] Quintiles of technical inefficiency estimates are created using our benchmark specification that employs true values of plot size (GPS).

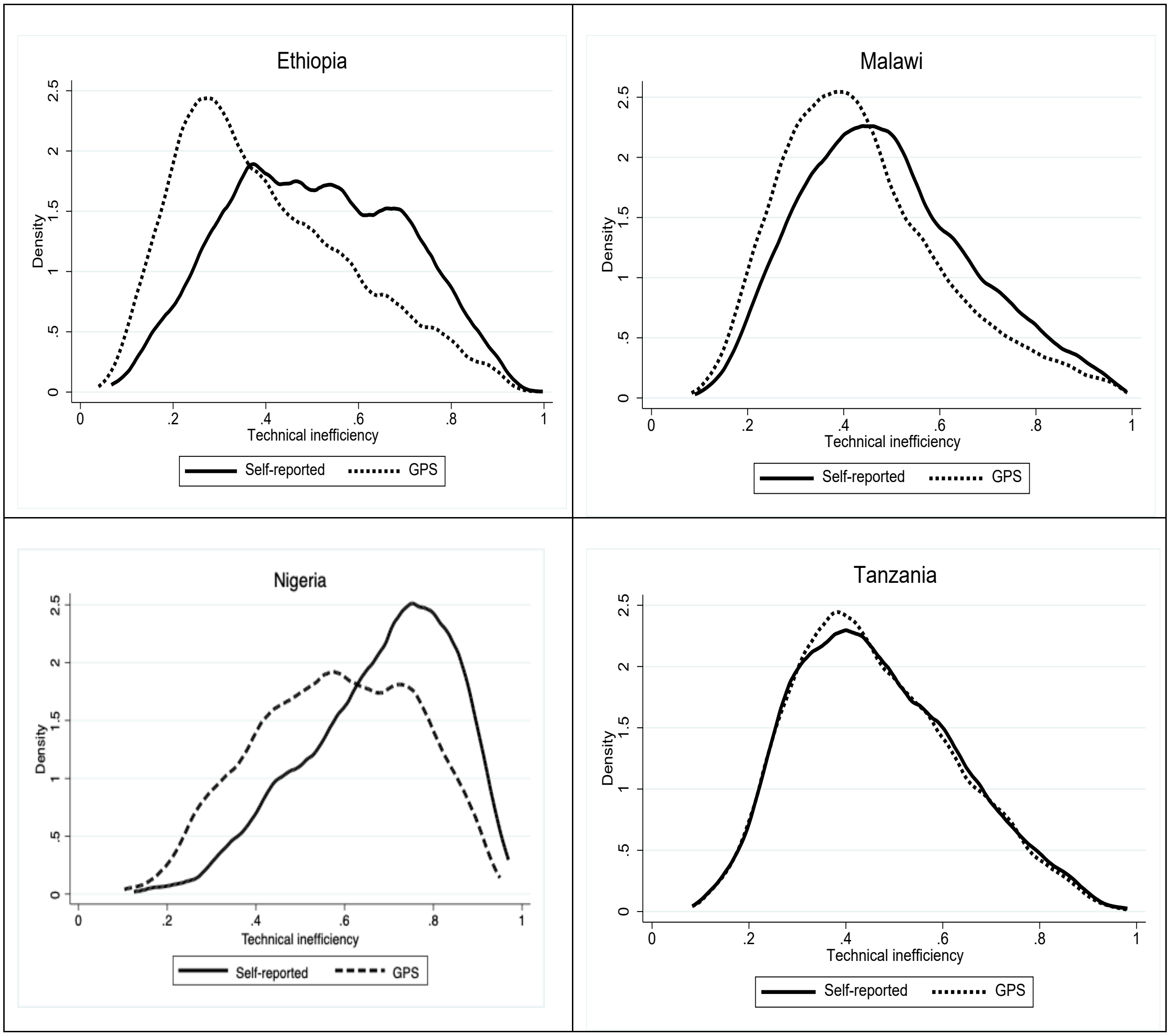
technical efficiency. The graphs in Figure 2 clearly show that measurement error in land area significantly shifts the distribution of technical inefficiency estimates. This is more so for Ethiopia and Nigeria, which is consistent with the significant differences in elasticities reported in Table 4. These graphs suggest that mismeasurement in land area leads to significant overestimation (underestimation) of actual inefficiency for those least inefficient (most inefficient) farmers. Overall, these results indicate that potential inaccuracies in agricultural inputs may contribute to existing estimates of high levels of technical inefficiency in African agriculture. Intuitively, this implies that what is commonly attributed to farmer inefficiency may be an artifact of mismeasurement in agricultural data. This is consistent with the findings in Gollin and Udry (2021) who found that part of the commonly estimated large factor misallocation in African agriculture is driven by mismeasurement in agricultural inputs.

Table 5: Technical inefficiency estimates using self-reported and GPS-based plot size

	Self-reported	GPS
	Panel A: Ethiopia	
Mean	0.50	0.40
Median	0.50	0.36
Bottom quintile	0.29	0.19
Top quintile	0.73	0.67
	Panel B: Malawi	
Mean	0.49	0.44
Median	0.47	0.41
Bottom quintile	0.29	0.25
Top quintile	0.72	0.68
	Panel C: Nigeria	
Mean	0.68	0.58
Median	0.70	0.58
Bottom quintile	0.48	0.35
Top quintile	0.85	0.80
	Panel D: Tanzania	
Mean	0.47	0.46
Median	0.45	0.44
Bottom quintile	0.28	0.27
Top quintile	0.69	0.69

Notes: This table provides alternative values of smallholders' technical inefficiency assuming that farmers' technical efficiency varies across years.

Figure 2: Mismeasurement in plot size and distribution of technical inefficiency estimates



5.2 Variety misclassification

In this section, we report results from the second mismeasurement case, crop variety misclassification using the CMS data, which provide DNA and self-reported based cassava variety information. As described in Section 2, we are particularly interested in examining the implications of variety misclassification on inference related to technical inefficiency. Following a similar structure to Table 4, we report estimates of the stochastic production function in Table 6. For comparison purposes, estimates reported in columns 1 and 2 are based on self-reported variety information controlling for self-reported and GPS measured plot size, respectively. In column 3, estimates are based on cassava variety identification using DNA-fingerprinting and GPS measured plot size. For each cassava plot, both the self-reported and DNA-fingerprinting indicators receive a value of one if the variety is identified as improved and zero otherwise. Estimates reported in Table 6 suggest that variety misclassification generates significant downward bias in technological parameters.[21] For instance, the results in the first column of Table 6 show that using improved crop variety is associated with a 60 percent increase in cassava production while the corresponding estimate based on DNA-fingerprinting is about 75 percent.

Table 6: Stochastic production frontier estimates using alternative measures of crop variety

Explanatory variables	Self-reported variety and area	Self-reported variety and GPS area	DNA and GPS
Improved variety (Self-reported)	0.598***	0.546***	
	(0.045)	(0.040)	
Improved variety (DNA)			0.749***
			(0.038)
Other inputs	Yes	Yes	Yes
Socioeconomic controls	Yes	Yes	Yes
Plot-level characteristics	Yes	Yes	Yes
Log-likelihood value	-5997.1	-5546.8	-5458.3
No. observations	4122	4122	4122

Notes. The dependent variable in this table is log-transformed production (measured in kg). Standard errors are given in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. DNA stands for crop variety identification using DNA-fingerprinting; GPS represents plot size measured using handheld GPS devices. All regressions control for those household and plot-level characteristics listed in Table 2 as well as year and crop fixed effects. Standard errors are given in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

In Table 7, we report estimates of technical inefficiencies (predicted assuming plot-invariant technical inefficiency). The values reported in each column are computed using the respective technological parameters in Table 6. Comparison of the mean value of technical inefficiencies suggests that failure to account for variety misclassification leads to inflated mean technical inefficiency estimates. For instance, the mean and median technical inefficiency estimates using self-reported variety and plot size are inflated by about 26-29 percent relative to

[21] Full results are given in Table A6 in Appendix.

the benchmark (based on DNA and GPS). Such overestimation is more acute among the bottom quintile (least inefficient) farmers. In particular, using self-reported variety and plot size data inflates the estimated technical inefficiency of the bottom and top quintile farmers by about 68 percent (23 percentage point) and 9 percent (7 percentage point), respectively.

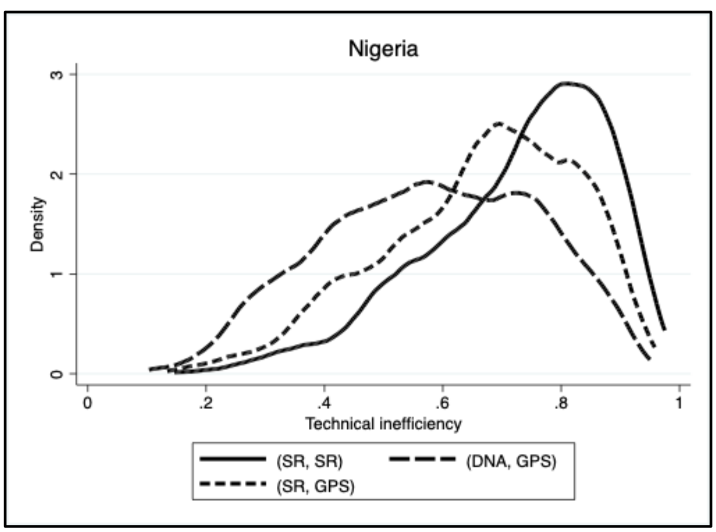
Table 7: Technical inefficiency estimates using self-reported and DNA-based variety information

	Self-reported variety and area	Self-reported variety and GPS area	DNA and GPS
Mean	0.73	0.66	0.58
Median	0.76	0.68	0.59
Bottom quintile	0.57	0.47	0.34
Top quintile	0.87	0.84	0.80

Notes: This table provides alternative values of technical inefficiency estimates assuming that farmers' technical efficiency is plot-invariant.

Figure 3 provides the kernel density distribution of technical inefficiency estimates using the different combinations of crop variety and plot size measures. This figure clearly suggests that variety misclassification and area mismeasurement distort the distribution of technical inefficiency estimates. As was the case previously, here again we see that variety misclassification and area mismeasurement lead to significant overestimation of inefficiency for the least inefficient farmers.

Figure 3: Variety misclassification and distribution of technical inefficiency estimates



Notes: This figure shows kernel density distribution of farmers' technical inefficiency estimated using alternative measures of plot size and crop variety identification. (SR, SR) stands for self-reported crop variety and self-reported plot size. (SR, GPS) stands for self-reported crop variety and objectively measured plot size (using GPS). (DNA, GPS) represents crop variety identification using DNA-fingerprinting and plot size measured using GPS devices.

5.3 Mismeasurement in production data

Thus far, we have assumed that self-reported production data are measured without error, an assumption we relax here as self-reported production data are also known to suffer from systematic measurement error (Desiere and Jolliffe, 2018; Gourlay et al., 2019; Abay et al., 2019). We, thus, employ crop-cut based production data along with plot size measured by GPS devices to estimate technical inefficiency. The analysis in this section serves two main purposes. First, this enables to examine the implication of measurement error in production data. We thus estimate technical inefficiency using both self-reported and objectively measured production data. Second, we examine whether the key results reported in Section 5.1 are driven by measurement error in production data or correlated measurement error in input and output data. For this purpose, we estimate technical inefficiency using objective and self-reported measures of production and plot size.

We follow the same estimation procedure as in Section 5.1 and production function elasticities are reported in Table 8. The first column in Table 8 provides estimates of stochastic production frontier using self-reported plot size and production, along with additional controls. The second column uses objectively measured plot size and self-reported production while the third column employs objectively measured production and self-reported land area. The fourth column employs objectively measured production and land area, the preferred specification when measurement error in inputs and production data are driven by survey errors (misreporting). The log-likelihood values of increases as we depart from self-report to objective measures of plot size and production, suggesting that actual production is relatively more responsive to true measure and size of inputs than self-reported values.

Comparing the output elasticities in Table 8 across alternative measurement scenarios reveal that the contribution of land resources substantially varies across measurement methods. For instance, the first column in Table 8 shows that a 1% increase in plot size is associated with about 0.6% increase in harvest when using self-reported land area and production data, while this almost doubles and amounts 1.1% when using objectively measured plot size and production data. This implies that using self-reported input and output data underestimates the marginal contribution of land resources (Abay, 2020). This underestimation in the marginal contribution of inputs is likely to lead to an overestimation of smallholders' technical inefficiency because the difference between farmers' production frontier and actual production, the estimated technical inefficiency, is expected to be larger than its true value.

Table 8: Stochastic production frontier estimates using self-reported and objective measures

Explanatory variables	(1) (SR, SR)	(2) (SR, GPS)	(3) (CC, SR)	(4) (CC, GPS)
Log (plot size: SR)	0.586***		0.835***	
	(0.013)		(0.012)	
Log (plot size: GPS)		0.659***		1.070***
		(0.012)		(0.009)
Year dummies	Yes	Yes	Yes	Yes
Other inputs	Yes	Yes	Yes	Yes
Socioeconomic controls	Yes	Yes	Yes	Yes
Plot-level characteristics	Yes	Yes	Yes	Yes
Log-likelihood value	-11389.9	-11103.7	-10830.8	-8824.8
No. observations	7310	7310	7310	7310

Notes. SR=self-reported; CC=crop-cut. The dependent variable in this table is log-transformed production (kg), measured either through self-reporting or crop-cutting exercise. The first two columns use self-reported production while the remaining columns are based on crop-cut harvest. Standard errors are given in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 9 summarizes different values of farmers' technical inefficiency computed using both self-reported and objectively measured data. Consistent with the results in Section 5.1 and 5.2, using self-reported production and land area substantially overestimates farmers' technical inefficiency. For instance, the first two columns of Table 9 show that average values of technical inefficiency are overestimated by about 18 percent (about 9 percentage point absolute differences) when estimated using self-reported production and land area. This is more acute for the bottom quintile (least inefficient) farmers, where self-reported data overestimate technical inefficiency of farmers by about 85 percent (23 percentage points).

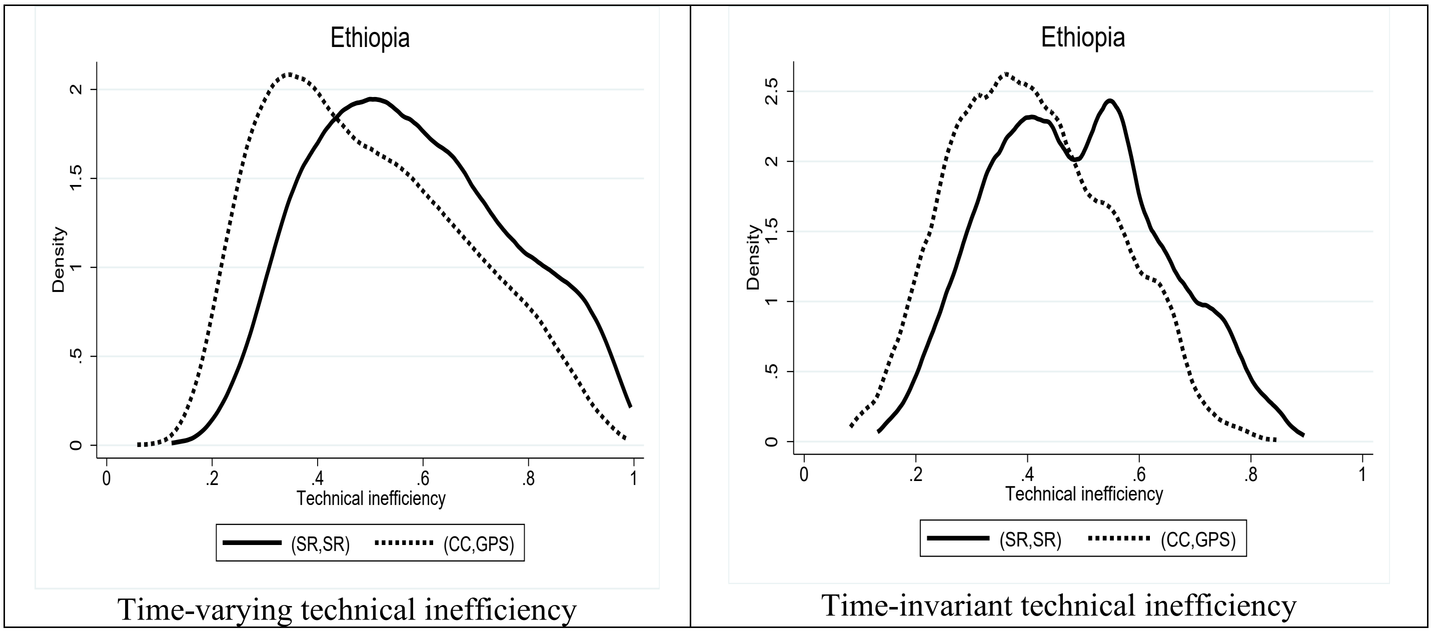
Table 9: Technical inefficiency estimates using alternative measures of plot size and production

Time-varying technical inefficiency			Time-invariant technical inefficiency	
	(SR, SR)	(CC, GPS)	(SR, SR)	(CC, GPS)
Mean	0.58	0.49	0.48	0.41
Median	0.57	0.47	0.47	0.40
Bottom quintile	0.50	0.27	0.41	0.23
Top quintile	0.67	0.75	0.57	0.60

Notes: This table provides alternative values of smallholders' technical inefficiency considering alternative measurements and assumptions about the nature of farmers' production efficiency. The first two columns in this table computes smallholders' technical inefficiency assuming that farmers' efficiency vary across years, while the next two columns are computed assuming time-invariant skills and efficiency. SR=self-reported; GPS=Global Positioning System; CC=crop-cut.

In Figure 4, we plot the distribution of farmers' technical inefficiency computed using self-reported and objectively measured data. We can clearly observe distinct patterns in the distribution of technical inefficiencies computed using different measurement methods. Most importantly, all computations based on self-reported land area and production data significantly overestimate (underestimate) actual technical inefficiency of least inefficient (most inefficient) farmers.

Figure 4: Mismeasurement in agricultural data and distribution of technical inefficiency estimates



Notes: The graphs in this figure show kernel density distribution of farmers' technical inefficiency. The first graph assumes and computes time-varying technical inefficiency. In the second graph we assume and compute time-invariant technical inefficiency. (SR, SR) stands for self-reported production and plot size, while (CC, GPS) shows objectively measured production and plot size, with production measurement coming from crop cuts (CC) and plot size measured using GPS receivers.

6. Conclusions

Empirical characterizations of smallholder agricultural production in sub-Saharan Africa have generally indicated high levels of technical inefficiency. However, these assessments have typically been based on self-reported agricultural inputs and production data, which are now known to suffer from various forms of measurement error. We have examined the implication of measurement error in agricultural input and output on estimation of technical inefficiency. We show that measurement error introduces multiple sources of bias in stochastic frontier production function estimation, making measurement error in these settings much more difficult to address than in linear regression models. The evidence we present, drawn from survey data from Ethiopia, Malawi, Nigeria and Tanzania, suggests that the commonly reported high levels of technical inefficiency in sub-Saharan Africa may be significant overestimates of actual inefficiency levels. In our sample, we find that technical inefficiency levels are overestimated by as much as 85 percent when using self-reported data instead of objective measures. Our results are consistent with Gollin and Udry (2021) who show that measurement error and heterogeneity account for a large share of what is commonly attributed to allocative inefficiency in self-reported data.

While our results are consistent across countries from different regions of Africa, suggesting external validity, more empirical studies of these relationships across a greater range of conditions would still be useful. Some internal validity concerns should also be acknowledged. In particular, our efficiency estimates are only as good as our assumptions about the nature of measurement error and the parametric assumptions associated with the stochastic production function we estimate. Therefore, the sensitivity of these parameter estimates to mismeasurement is potentially compromised by inherent weaknesses in the standard parametric stochastic production frontier modelling approach. Future studies using non-parametric approaches may provide additional insights on how measurement error affects estimation of technical inefficiency. A second issue is our maintenance of the standard assumption that input choices are orthogonal to inherent efficiency levels. Future studies relying on exogenous variation in agricultural inputs may help confirm our findings.

Our results have implications for evidence-based agricultural policy making in Africa. Technical inefficiency in smallholder production is the basis for policy guidance to redress many apparent barriers to production efficiency (e.g., via improved extension, training, and education). If the most binding constraints to improved agricultural outcomes are actually elsewhere – for example if they are associated with other technological constraints – then scarce development resources and monitoring efforts are rendered less effective. Furthermore, if the spatial, demographic or other distributional patterns of biases in inefficiency estimates are significant (the exploration of which we leave to future work), then targeting efforts will suffer as a consequence. For resource-strapped countries in sub-Saharan Africa, where agricultural performance gains are sorely needed, such mistargeting is potentially very costly in terms of foregone welfare of poor rural households.

More accurate diagnosis of smallholder production efficiency will require improved measurement of agricultural inputs and other data. This implies increased investments in data collection by national governments and their development partners. In the short term, such additional investments may focus on identifying methodological innovations that can reduce mismeasurement in agricultural data. Such investments in data quality should reduce bias in productivity diagnostics and hence improve targeting of productivity enhancing technologies and investments.

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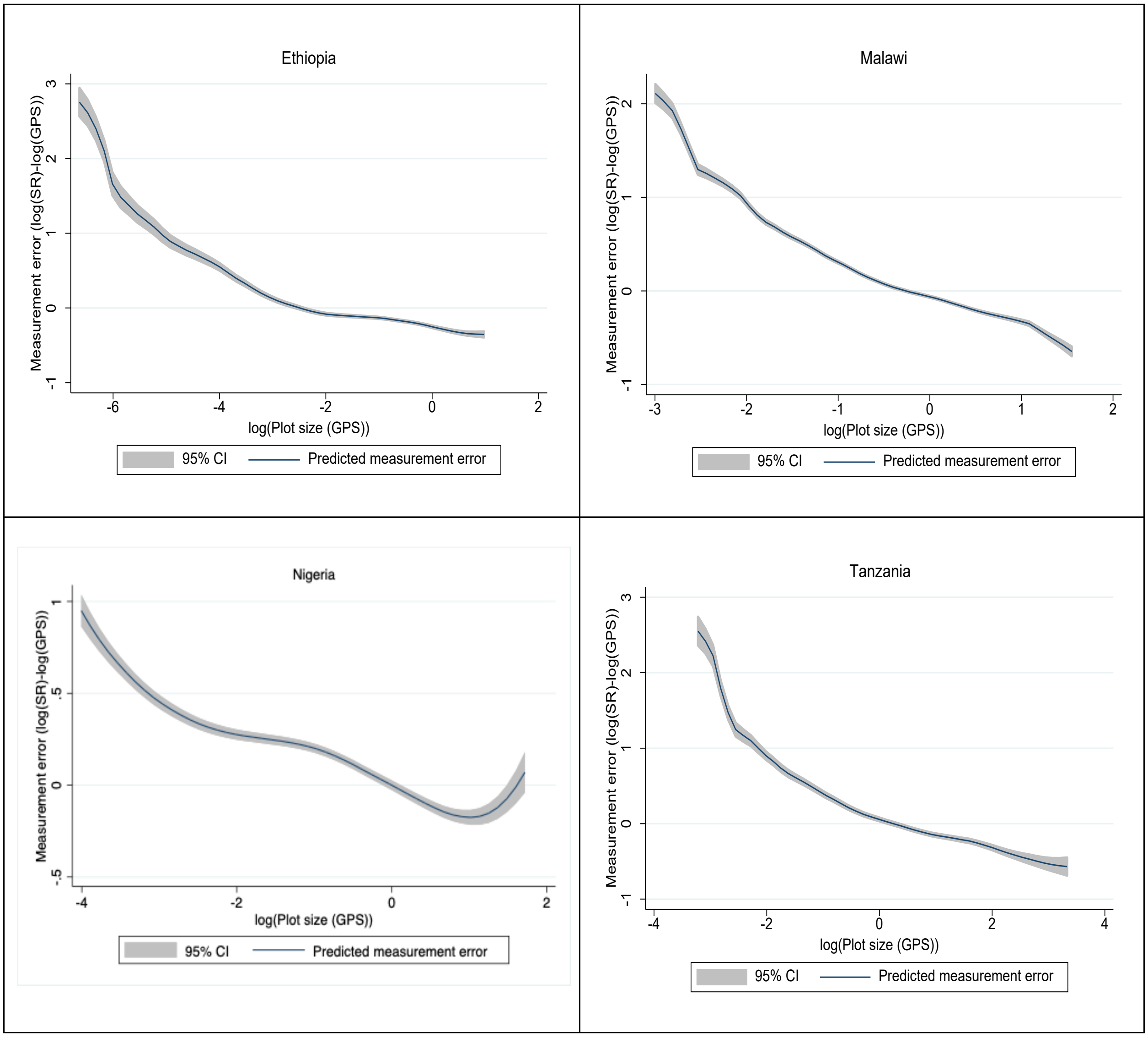
Appendix

Figures and Tables

Figure A1: Distribution of measurement error in self-reported plot size



Notes: Relationships between measurement error in self-reported and true plot size. We define measurement error in relative terms as the log(self-reported plot size)-log(GPS-based plot size).

Table A1: Stochastic production frontier estimates using alternative measures of plot size (Ethiopia)

Explanatory variables	(1) Self-reported	(2) GPS
Log (plot size: SR)	0.456***	
	(0.006)	
Log (plot size: GPS)		0.509***
		(0.006)
Household head is male (1=yes)	0.068**	0.050**
	(0.028)	(0.025)
Log(age of household head)	0.017	-0.023
	(0.033)	(0.030)
Household head literate (1=yes)	-0.007	-0.007
	(0.022)	(0.020)
Household size	0.007	0.002
	(0.005)	(0.004)
Farm size per capita (1=yes)	0.096***	0.043***
	(0.015)	(0.013)
Irrigated plot (1=yes)	0.255***	0.168***
	(0.042)	(0.040)
Soil quality good (1=yes)	0.082***	0.083***
	(0.018)	(0.017)
Steep slope plot (1=yes)	-0.050**	-0.087***
	(0.023)	(0.022)
Pure stand cropping (1=yes)	-0.236***	-0.181***
	(0.017)	(0.017)
Log (labor days applied)	0.173***	0.124***
	(0.007)	(0.006)
Fertilizer (1=yes)	0.353***	0.309***
	(0.019)	(0.018)
Improved seed (1=yes)	0.197***	0.158***
	(0.025)	(0.024)
Pesticide/herbicide (1=yes)	0.266***	0.252***
	(0.024)	(0.023)
Year dummies	Yes	Yes
Crop dummies	Yes	Yes
Log-likelihood value	-39791.9	-38718.6
No. observations	26890	26890

Table A2: Stochastic production frontier estimates using alternative measures of plot size (Malawi)

Explanatory variables	(1) Self-reported	(2) GPS
Log (plot size: SR)	0.543***	
	(0.011)	
Log (plot size: GPS)		0.527***
		(0.009)
Household head is male (1=yes)	0.262***	0.241***
	(0.019)	(0.018)
Log(age of household head)	0.133***	0.118***
	(0.022)	(0.022)
Household head literate (1=yes)	0.101***	0.131***
	(0.024)	(0.023)
Household size	0.044***	0.032***
	(0.004)	(0.004)
Farm size per capita	0.024***	-0.033***
	(0.009)	(0.007)
Irrigated plot (1=yes)	0.089	0.210**
	(0.100)	(0.098)
Soil quality good (1=yes)	0.200***	0.200***
	(0.015)	(0.015)
Steep slope plot (1=yes)	-0.034**	-0.032**
	(0.015)	(0.015)
Log (labor days applied)	0.022***	0.009**
	(0.005)	(0.005)
Fertilizer (1=yes)	0.121***	0.094***
	(0.016)	(0.015)
Improved seed (1=yes)	-0.031	-0.028
	(0.031)	(0.031)
Pesticide/herbicide (1=yes)	0.243***	0.203***
	(0.051)	(0.051)
Year dummies	Yes	Yes
Crop dummies	Yes	Yes
Log-likelihood value	-49640.4	-49224.5
No. observations	30785	30785

Notes. The dependent variable in this table is log-transformed production (measured in kg). SR stands for self-reported plot size; GPS represents plot size measured using handheld GPS devices. All regressions control for year and crop fixed effects. Standard errors are given in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A3: Stochastic production frontier estimates using alternative measures of plot size (Nigeria)

Explanatory variables	(1) Self-reported	(2) GPS
Log (plot size: SR)	0.374***	
	(0.019)	
Log (plot size: GPS)		0.652***
		(0.016)
Household head is male (1=yes)	0.264***	0.226***
	(0.073)	(0.064)
Log(age of household head)	-0.116	0.035
	(0.088)	(0.077)
Household head literate (1=yes)	0.157**	0.123**
	(0.070)	(0.061)
Household size	0.026**	0.021**
	(0.010)	(0.009)
Soil quality good (1=yes)	0.175***	0.113***
	(0.045)	(0.040)
Pure stand cropping (1=yes)	-0.024	0.016
	(0.034)	(0.030)
Plot managed jointly (1=yes)	-0.053	-0.042
	(0.044)	(0.039)
Log (labor days applied)	0.479***	0.109***
	(0.025)	(0.024)
Fertilizer (1=yes)	0.023	0.109***
	(0.046)	(0.040)
Improved seed (1=yes)	0.803***	0.749***
	(0.043)	(0.038)
Pesticide/herbicide (1=yes)	0.134***	0.048
	(0.048)	(0.043)
Log-likelihood value	-5918.774	-5458.265
No. observations	4122	4122

Notes. The dependent variable in this table is log-transformed production (measured in kg). SR stands for self-reported plot size; GPS represents plot size measured using GPS devices. Standard errors are given in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A4: Stochastic production frontier estimates using alternative measures of plot size (Tanzania)

Explanatory variables	(1) Self-reported	(2) GPS
Log (plot size: SR)	0.463***	
	(0.014)	
Log (plot size: GPS)		0.396***
		(0.012)
Household head is male (1=yes)	0.099***	0.108***
	(0.033)	(0.033)
Age of household head (years)	0.007**	0.008**
	(0.003)	(0.003)
Household head literate (1=yes)	-0.340***	-0.335***
	(0.043)	(0.042)
Household size	0.029***	0.028***
	(0.004)	(0.004)
Farm size per capita	0.015**	0.008
	(0.006)	(0.006)
Irrigated plot (1=yes)	0.589***	0.609***
	(0.079)	(0.079)
Soil quality good (1=yes)	0.246***	0.254***
	(0.025)	(0.024)
Steep slope plot (1=yes)	0.001	-0.004
	(0.026)	(0.026)
Pure stand cropping (1=yes)	0.562***	0.574***
	(0.033)	(0.033)
Log (labor days applied)	0.272***	0.258***
	(0.015)	(0.015)
Fertilizer (1=yes)	0.536***	0.515***
	(0.037)	(0.036)
Improved seed (1=yes)	0.186***	0.203***
	(0.032)	(0.032)
Pesticide/herbicide (1=yes)	0.465***	0.424***
	(0.091)	(0.090)
Year dummies	Yes	Yes
Crop dummies	Yes	Yes
Log-likelihood value	-10132.0	-10083.2
No. observations	7255	7255

Notes. The dependent variable in this table is log-transformed production (measured in kg). SR stands for self-reported plot size; GPS represents plot size measured using handheld GPS devices. All regressions control year and crop fixed effects. Standard errors are given in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A5: Time-invariant technical inefficiency estimates using self-reported and GPS-based plot size

	Self-reported	GPS
Panel A: Ethiopia		
Mean	0.58	0.47
Median	0.60	0.47
Bottom quintile	0.38	0.26
Top quintile	0.75	0.68
Panel B: Malawi		
Mean	0.49	0.44
Median	0.47	0.42
Bottom quintile	0.28	0.25
Top quintile	0.72	0.68
Panel C: Tanzania		
Mean	0.50	0.50
Median	0.49	0.49
Bottom quintile	0.31	0.30
Top quintile	0.72	0.72

Notes: This table provides alternative values of smallholders' technical inefficiency assuming time-invariant efficiency.

Table A6: Stochastic production frontier estimates using alternative measures of crop variety (Nigeria)

Explanatory variables	(1) Self-reported variety and area	(2) Self-reported variety and GPS area	(3) DNA and GPS
Improved variety (Self-reported)	0.598***	0.546***	
	(0.045)	(0.040)	
Improved variety (DNA)			0.749***
			(0.038)
Household head is male (1=yes)	0.169**	0.148**	0.226***
	(0.075)	(0.067)	(0.064)
Log(age of household head)	-0.089	0.068	0.035
	(0.091)	(0.081)	(0.077)
Household head literate (1=yes)	0.159**	0.125*	0.123**
	(0.072)	(0.064)	(0.061)
Household size	0.025**	0.021**	0.021**
	(0.010)	(0.009)	(0.009)
Log (plot size: SR)	0.384***		
	(0.019)		
Log (plot size: GPS)		0.662***	0.652***
		(0.017)	(0.016)
Soil quality good (1=yes)	0.157***	0.092**	0.113***
	(0.046)	(0.041)	(0.040)
Pure stand cropping (1=yes)	-0.044	-0.002	0.016
	(0.035)	(0.031)	(0.030)
Plot managed jointly (1=yes)	-0.042	-0.035	-0.042
	(0.046)	(0.041)	(0.039)
Log (labor days applied)	0.484***	0.099***	0.109***
	(0.026)	(0.025)	(0.024)
Fertilizer (1=yes)	-0.006	0.091**	0.109***
	(0.047)	(0.042)	(0.040)
Pesticide/herbicide (1=yes)	0.160***	0.067	0.048
	(0.049)	(0.044)	(0.043)
Log-likelihood value	-5997.10	-5546.77	-5458.27
No. observations	4122	4122	4122

Notes. The dependent variable in this table is log-transformed production (measured in kg). SR stands for self-reported plot size; GPS represents plot size measured using handheld GPS devices. Standard errors are given in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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