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Are farmers 'efficient but poor'? The impact of crop choices on technical efficiency and poverty in Nigeria

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Abstract

We test the 'efficient-but-poor' hypothesis by estimating the determinants of smallholders' choice over cash or food crops and whether their crop choice affects technical efficiency and poverty using the national household panel data in Nigeria. We employ the stochastic frontier analyses correcting for sample selection about farmers' crop choice. Our results indicate that smallholders are generally efficient in their resource allocations. A treatment effects model is employed to estimate farmers' crop choice in the first stage and the impact of their choices on technical efficiency and poverty outcomes in the second stage. The results show that farmers' access to free inputs, non-farm income and the use of seeds from the previous growing season are important determinants of crop choice. The adoption of cash crops by food-crop producing households will not generally reduce poverty, although it will improve technical efficiency marginally. However, if cash crops are commercialised, poverty tends to decline.

KEYWORDS

crop choice, Nigeria, poverty, stochastic frontier analysis, technical efficiency, treatment effects model

JEL CLASSIFICATION

D24; I32; N57; 013; 033

1 | INTRODUCTION

The main purpose of this study is to test the 'efficient-but-poor' hypothesis[1] by estimating the determinants of smallholders' crop choices and whether their 'endogenous' crop choices affect technical efficiency and consumption poverty. We focus on farmers' choice between cash crops and food crops where the former is defined based on the crop's exportability. Separately, we also analyse the effect of the extent to which cash or food crops are commercialised on technical efficiency and consumption poverty.

The challenge in estimating the effect of crop choice on technical efficiency is that crop choice is endogenous, since farmers' crop choice is also influenced by the resulting revenue from the crop. To address this issue, our stochastic frontier analyses (SFA) are corrected for sample selection in estimating farmers' technical efficiency, following Greene (2010). We use household panel data constructed from two waves of Nigeria's General Household Survey-Panel, which is part of the World Bank's Living Standards Measurement Study. This, to our knowledge, is the first application of corrected SFA to Nigeria and one of the few applications to the agricultural productivity of households in developing countries.[2]

Producing cash crops was traditionally regarded as the forte of large-scale commercial farmers. However, there has been an argument in recent years that smallholder farmers could also take advantage of the large international market with cash products, hence raising overall productivity and improving their farming incomes. We examine this argument in greater detail by asking the following research questions: 'Have smallholder farmers who chose to grow a specific type of crops, such as cash crops with a higher degree of exportability, improved their technical efficiency and reduced poverty?' and 'How did commercialisation of each type of crop—cash or food—influence technical efficiency and poverty?' In answering these questions, we also explore the underlying reasons for choosing to grow specific types of crops as well as the mechanisms for achieving, or not achieving, better technical efficiency or reducing, or not reducing, household poverty.

Nigeria has been selected because it is a country where the agricultural sector is trapped in a cycle of low productivity. Nigeria is classified as a lower-middle-income country with a national GDP of US\$449.1 billion as of 2019 (which is about 0.5% of the global economy), an estimated population of 201 million people, and a gross national per capita GDP of US\$2230 (World Bank, 2021). The average growth rate of Nigeria's GDP between 2007 and 2014 was 6.5%, which is higher than the average of sub-Saharan African countries (4.8%, excluding high-income countries) and European Union countries whose growth rate was only 0.6% in the same period. However, there has been a sharp decline in the GDP growth rate of Nigeria since then to an average of 0.6% between 2015 and 2017 due to a period of severe recession in 2016, after which it remained at around 2% in 2018 and 2019 (World Bank, 2021).

Despite the long period of high economic growth of Nigeria, about 23% (42%) of the population lived on less than US\$1.90 (US\$3.20) a day in 2009 at 2011 PPP (World Bank, 2021). In 2017 Nigeria overtook India as the country with the largest amount of absolute poverty in the world; with a large proportion of the poor engaged in agriculture. Agriculture accounts for

[1]'The poor but efficient hypothesis'—which is sometimes called 'theory', 'proposition', or 'argument' by different scholars—was put forward by the Nobel laureate, Theodore Schultz (Schultz, 1964). It implies that farmers engaged in traditional agriculture are often poor with only a small area of land—either rented or owned. Given the monopolistic and collusive land market in developing countries, they cannot easily get out of poverty due to both difficulties in undertaking the new investment as well as the low rate of returns to agricultural investment (e.g., Lundahl, 1987). However, Schultz 'hypothesised' that smallholders in traditional agriculture are highly efficient in terms of their resource allocations within these constraints, contrary to the previously held view that they are constrained by tradition or culture (Abler & Sukhatme, 2006).

[2]Previous applications include Rahman (2011) and Martey et al. (2019).

TABLE 1 Selected crops with outputs, prices and expected revenues

Crop	Land area ('000 ha)	Output ('000 metric tons)	Avg. price per kg (naira)	Avg. revenue per ha ('000 naira)
Yam	3236.2	37328.2	76.1	877.4
Cassava	3481.9	42533.2	65.3	797.8
Cocoyam	520.1	2957.1	80.0	454.8
Cotton	398.6	602.4	230.2	348.0
Melon	469.7	507.3	123.1	132.9
Rice	2432.6	4472.5	72.0	132.4
Maize	4149.3	7676.9	64.7	119.6
Guinea corn	4960.1	7141.0	73.1	105.2
Beans	2859.8	3368.2	83.0	97.8
Groundnut	2785.2	3799.2	69.0	94.2
Soyabeans	291.4	365.1	60.0	75.2
Millet	4364.2	5170.5	58.5	69.3

Source: Nigerian Bureau of Statistics (NBS), 2009.

about 40% of the country's GDP and employs about 65% of the people (World Bank, 2021). Thus, the agricultural sector is important in determining the quality of life and welfare of a large proportion of people in the country. However, it has lagged behind other sectors and the rest of the world in terms of productivity.

The low agricultural productivity in Nigeria could be caused by many factors ranging from poor soil quality exacerbated by erosion, pollution and leaching, to scarcity and high cost of inputs, and including the continued use of traditional farming practices. However, we focus on the effects of crop choice, which is directly under the farmer's control, to examine the 'efficient-but-poor' hypothesis.

To illustrate this point briefly, Table 1 summarises the Nigerian averages for area planted, prices, average output (in tonnes) and average revenues per hectare for selected crops. This shows that output and revenues per hectare vary considerably across different crops. The cross-crop variations in the use of inputs, for example, land, to achieve a certain level of revenues supports our focus on differences in technical efficiency across different crops.

This research is important for several reasons. Firstly, our study provides policy-makers with insights into how the improvement in technical efficiency or poverty reduction is achieved by reallocating crops given the current set of available inputs and agricultural technology. Governments in Nigeria often seek to come up with an overarching agricultural agenda for the agricultural sector—for instance, encouraging the production of certain crops which it deems more 'important' (Iwuchukwu & Igbokwe, 2012). Drawing upon the large-scale national household survey dataset, we provide policy implications for the government on the agricultural policy regarding the promotion of particular crops. In addition, poverty and food security remain a major concern for many sub-Saharan African countries, including Nigeria. Cropping decisions can have far-reaching implications for national food security. If the production of certain crops is found to improve the welfare outcomes of farmers, such as poverty or food security, our results provide an important policy lesson.

The rest of this paper is organised as follows. The next section highlights recent empirical studies on productivity and the technical efficiency of smallholders and the effects of cropping decisions on productivity and welfare. Section 3 discusses our methodology, starting with how we define the key crop choice variables, and then presents our main econometric models, namely, SFA and the treatment effects model. Section 4 explains the data and Section 5 presents the main results. The final section concludes.

2 | LITERATURE REVIEW

2.1 | Agricultural productivity and technical efficiency in Nigeria

Technical efficiency is defined as the farmer's 'ability to produce maximum output given a set of inputs and technology' (Bravo-Ureta et al., 2007, p. 58), which is measured empirically by 'the ratio of the produced output of an agricultural household over the maximally possible output, given a set level of inputs'. It takes the value between 0 and 1 where the higher value implies more efficient use of inputs given the agricultural technology. Stochastic frontier models have been most commonly used to measure agricultural farmers' technical efficiency. For Nigeria, these models have been used to compute farmers' technical efficiency for a large variety of crops including rice, wheat and cassava, among others (Adeyemo et al., 2010; Amaza et al., 2006; Ebong et al., 2009; Onyenweaku & Ohajianya, 2009). We also apply the stochastic frontier method, not for specific crops, but for a group of crops with the same characteristics as discussed below. In addition, we use panel data and take account of unobservable household characteristics.

For example, Adeyemo et al. (2010) compute an average technical efficiency (TE) score of 0.89 for cassava farmers in Ogun state, while Ebong et al. (2009) do the same for food crop farmers in Akwa Ibom and find an average TE of 0.81. In the south-east region, Onyenweaku and Ohajianya (2009) calculate an efficiency score of 0.65 for rice farmers in Ebonyi state. Finally, Amaza et al. (2006) do the same for food crop producers in Borno and calculate an average score of 0.68. Studies such as these are an indication of the range of calculated efficiency scores in particular regions. We conduct a nationwide analysis using nationally representative household panel data of Nigeria. To the best of our knowledge, this is the first study in which the nationwide panel dataset is used with SFA to estimate technical efficiencies.

2.2 | Crop choice, productivity and welfare in developing countries

In the papers we review, household welfare is measured by domestic household per capita consumption. Using national household surveys from Mali, Delarue et al. (2009) studied the relationship between cotton production and household consumption and discovered that cotton producers consumed 9% more food on average than non-cotton-producing households where food consumption is a proxy for total consumption. When the authors disaggregated the results by the farm size, they found, not unexpectedly, that the largest cotton producers consume up to 22% more than the smallest producers, though these results imply correlations rather than causation. Loveridge et al. (2002) carried out a similar analysis of coffee for Rwanda and found a weak positive relationship between coffee production and the consumption outcomes of households. They speculated that this weakness could be explained by the low prices for coffee in the world market at the time of the survey, 2001. Murekezi and Loveridge (2009) use the same methodology to compare the 2001 season data of Rwanda to that of 2007, to assess the impact of policy reforms and found that technology could be a factor in the efficiency of cash-cropping among smallholders, since those using modern techniques spent 15% more on food and 17% more on all goods than the traditional producers. We also take account of differences in production technologies by distinguishing crops that are produced by different methods of production from each other depending on the type of crops (i.e., cash and food crops). Similarly, Maertens and Swinnen (2009) found that the welfare of rural households substantially improved through producing high-yield vegetables for export in Senegal.

3 | METHODOLOGY

3.1 | Defining crop choice

Our research questions are: 'Does choosing to grow a particular type of crop result in a higher level of technical efficiency and better household welfare outcomes or lower levels of household poverty?'—that is, 'the cash vs food-crop debate'. A cash crop is broadly defined as a crop that is grown primarily for sale. Food crops, on the other hand, are grown primarily for household consumption. However, in the literature, the term 'cash crop', specifically denotes crops for export and does not necessarily include crops for sale in the domestic and local markets. According to the US Environmental Protection Agency, cash crops are typically purchased by organisations or commercial entities separate from the farm.[3] Given these definitions, if crops were to be divided by such a straight classification, it could be confusing and perhaps impossible to empirically test using the real data. This is also important as our study intends to group similar crops rather than study farmers who grow specific crops. Therefore, we are more specific in our classification of crops.

Our main objective is to identify what determined the choice of crop. Furthermore, we need to capture the entire life cycle of the crop within one crop year. Therefore, we exclude all households with livestock and/or tree crops listed as their primary output in defining our crop choice model. This ensures that our comparisons will be restricted to annual crops (that is, the crops that can complete a life cycle within a crop year).

We also restrict attention to crops for which the data on export are fully available and there is likely to be a conflict in choosing between a food crop or a cash crop. For example, cassava is one of Nigeria's largest agricultural exports, with an average of over 45,000,000 metric tons exported per year on average, making the country the largest exporter of the product in the world. Cassava is often used in industry to produce ethanol and other biofuels. Therefore, we have classified farmers who produce cassava as cash-crop producers. It is clear that the type of crop produced alone does not determine how much of the farm product is marketed, so we have also included an index of commercialisation to identify how much produce is sold versus self-consumed as an interaction with the type of crop produced. Table 2 details our crop classifications. Given the difficulties, we have grouped 'representative' crops as either cash or food crops as in Table 2. It should be noted that this classification is *exclusive,* that is, all the crops in our analysis are defined as *either* Cash Crops (C_1), defined by the most representative cash crops, in terms of the overall share of exports, *or* Food Crops (C_2), defined by the most representative food crops, such as tuber and root crops and cereals.

3.1.1 | Cash crops (C_1)

To create the variable for the first category by most exported crops, FAO data were used to identify which Nigerian crops were most exported. Farmers who listed the top five exported

[3]See 'Ag 101: Crop Glossary' (2009), US Environmental Protection Agency.

TABLE 2 List of cash and food crops

Crops	Export ('000 metric tons)	% of sample (Wave 1)	% of sample (Wave 2)
Cash crops (C_1)			
Cassava	42,533.17	10.42	6.48
Sugarcane	1429.57	0.04	0.04
Cotton	533.31	0.16	0.19
Ginger	167.29	0.08	0.08
Sesame seed (Beni-seed)	127.60	0.36	0.35
Total (cash crops)	44790.94	11.06	7.14
Food crops (C_2)			
Yam	-	21.51	23.17
Maize	-	8.07	7.30
Rice	-	2.90	2.74
Cocoyam	-	1.49	1.71
Groundnuts	-	1.79	1.45
Potatoes	-	0.58	0.64
Ginger	-	0.08	0.08
Total (food crops)	-	36.42	37.09

Source: Authors' calculation based on the Nigerian LSMS data for 2011 and 2013.

crops as their primary product output were classified as cash-crop producing households. As can be seen from Table 2, 11% of our sample planted one of these five crops in the first wave and 7% planted these in the second wave.

3.1.2 | Food crops (C_2)

The major class of food crops is made up of tubers and roots, which have long been recognised as particularly important for the food security of households in developing countries, especially those in sub-Saharan African countries. Maize and rice are the only cereals included because they are the most commonly consumed by farm households; while the others have traditionally only been grown by large-scale farmers rather than smallholders, reflecting both lack of irrigation facilities and of sufficient financial capital (Grote et al., 2021), and data are also not readily available. According to the Commission for Africa Report (2010), tubers are an important component of the diet for 2.2 billion people in developing countries. In Nigeria, they serve traditionally as a store of wealth, the size of the yam barn indicating relative prosperity (Obidiegwu & Akpabio, 2017). Our analysis of the FAOSTAT dataset shows that, even though there has been an increase in the cereal area (rice and maize) since the 1980s, there has also been an increase in the roots and tubers area—and especially rapid recently (since 2009)—and that root and tuber yields are both greater than cereals, and have been increasing at a substantially greater rate in Nigeria since the 1980s.[4] However, notwithstanding their apparent importance, tuber and roots crops have not been given much attention in policy-making. Perhaps their bulk and high water content, and hence transport and storage difficulties constrain the development of value chains and marketability.

[4]See Figures A1 and A2 in Appendix S1 for details.

3.2 | Household commercialisation index (HCI)

In our empirical analyses, an index for the degree of commercialisation of crop production per household is used to capture the extent to which an agricultural household's crop production—regardless of whether being for cash crops or food crops—is oriented toward commercial agriculture. Following Govereh et al. (1999) and Von Braun et al. (1994), we calculate this index as the proportion of the total value of all production which is sold, resulting in an HCI of between 0 and 1.

$$HCI = \left[\frac{\textit{gross value of crop sales}}{\textit{gross value of all crop production}}\right] \times 100 \tag{1}$$

We interact HCI with both cash and food crop choice in our estimations, to capture the sales effect. Although this approach ignores the absolute value of crop sales, the measure is still useful for describing agriculture in developing countries like Nigeria. Smaller farms are more likely to consume a larger proportion of their total output rather than selling (except for cases of higher value-added crops like cut flowers or vegetables) (Govereh et al., 1999).

3.3 | Stochastic frontier analysis (with the Greene, 2010 correction for selection bias)

To estimate the technical efficiency of crop production, we aggregate the data at the household level. Aigner et al. (1977) and Meeusen and Van den Broeck (1977) show how the error term in a stochastic frontier model can be split into: v_i, the stochastic error term and u_i, the inefficiency error term. To illustrate, the base model takes the form:

$$\ln(Y_i) = \ln(f(\boldsymbol{X}_i)) + v_i - u_i \;\text{ with } u \geq 0 \tag{2}$$

where v_i is either positive or negative and is assumed to be normally distributed with a mean zero and constant variance, as v_i represents an unsystematic stochastic effect related to measurement errors and random influences (e.g., luck, drought, flood or other weather shocks). On the other hand, u_i is non-negative and either assumed to be half-normal or truncated normally distributed, measuring technical inefficiency, that is, the stochastic shortfall of output from the most efficient farm on the production frontier (Coelli & Battese, 1996). However, crop choice is likely to be endogenous. We have thus followed Greene (2010) who demonstrated that selection bias could make a significant difference if ignored in the computation of a production frontier. We estimated Greene's selection model for the stochastic frontier analysis in a panel data framework (Pitt & Lee, 1981) to take account of household unobservable heterogeneity.

Three conventional inputs are used in the computation of the agricultural production frontier function. These are *land* (total agricultural land area under cultivation), *labour* (total wage expenditures for labour including family labour[5]) and *inputs* (intermediate input costs like seed, fertiliser, pesticides, cost of irrigation and costs to rent farm equipment/machinery). To gain some perspective on the results of this analysis, it may be useful to examine the nature of land distribution in Nigeria, especially as it relates to agriculture.

In an ideal case, there would also be a variable for capital (the depreciated cost of machinery and buildings), but this is not included due to data constraints. However, this is not

[5]Family labour is costed by multiplying the number of hours supplied by family members with the market wage rate per hour.

a problem in our study context because most smallholders in Nigeria usually own very little capital (apart from small implements like hoes and shovels) and farmers wishing to mechanise tend to rent machines rather than purchase them. Rental costs are included in the inputs variable. These inputs are used to produce the output y_{it} defined as the total revenue generated at the farm level, including by-products. Both the Cobb–Douglas model[6] and the trans-log model have been estimated, but we have adopted the trans-log model as it is a more general specification and performs better for our data, based on the LL test (Table 4).

$$\begin{aligned}\ln\left(Y_{it}\right) = {} & \beta_0 + \beta_1 \ln(land) + \beta_2 \ln(labour) + \beta_3 \ln(other\ inputs) + \beta_4 \ln^2(land) \\ & + \beta_5 \ln^2(labour) + \beta_6 \ln^2(other\ inputs) + \beta_7 \ln(land)\ln(labour) \\ & + \beta_8 \ln(land)\ln(other\ inputs) + \beta_9 \ln(labour)\ln(other\ inputs) + v_{it} - u_{it}\end{aligned} \tag{3}$$

Because of the non-symmetry of the conventional error term, ε_{it}, the expected value is defined as $E\left(\varepsilon_{it}\right) = -E\left(\varepsilon_{it}\right) \leq 0, \varepsilon_{it} = v_{it} - u_{it}$. The estimation by OLS will provide inconsistent estimates of the parameters apart from the intercept and cannot extricate the technical efficiency component from its normal residual error. Hence, we use the maximum likelihood estimation (MLE). MLE selects values of the model parameters that produce the distribution most likely to have produced the observed data by maximising the likelihood function. We assume that the technical inefficiency error term (u_{it}) has a positive half-normal distribution and that u_{it} and v_{it} are independent so that the efficiency estimates will be in the range between 0 and 1. This is useful because the standard deviation of the distribution can concentrate the efficiencies near-zero or spread them out (with zero cut off) (Aigner et al., 1977; Street, 2003).

Technical efficiency can then be derived by Equation (3) for each agricultural household. It is the ratio of the output y_{it} over the stochastic frontier output when $u_{it} = 0$:

$$TE_{it} = \frac{y_{it}}{exp\left(x_{it}\beta + v_{it}\right)} = \frac{exp\left(x_{it}\beta + v_{it} - u_{it}\right)}{exp\left(x_{it}\beta + v_{it}\right)} = exp\left(-u_{it}\right) \tag{4}$$

3.4 | Treatment effects model

We now deal with the selection bias problem: the categorical variables for crop choice ($\mathbf{C_i}$) may well be subject to self-selection. There are likely to be unobservable household characteristics (e.g., entrepreneurship, psychological factors) that influence crop choice ($\mathbf{C_i}$,) so that $\mathbf{C_i}$ is endogenous as it is correlated with the error term of Equation (3).

We follow Greene (2010) and implement a treatment effects model, similar to the Heckit method (Heckman, 1979). We use a control function with an endogenous treatment variable which is the self-selection of crop type (namely, cash or food crops) made by a household. In addition, crop choice is likely to be an endogenous determinant of poverty and technical efficiency.

The treatment effects model estimates the effect of an endogenous binary treatment, $\boldsymbol{C}_{it}$ (the crop choice in a binary case at time t), on a continuous, fully observed outcome variable, $\boldsymbol{Y}_{it}$ (in this case technical efficiency or poverty in separate models); conditional on vectors of explanatory variables, $\boldsymbol{X}_{it}$ and $\boldsymbol{Z}_{it}$(which would include exclusion restrictions). This can be modelled as:

$$Y_{it} = \beta \boldsymbol{C}_{it} + \eta \boldsymbol{X}_{it} + \mu_i + v_{it} \tag{5}$$

[6]The Cobb–Douglas model is specified as: $\ln\left(Y_{it}\right) = \beta_0 + \beta_1 \ln(land) + \beta_2 \ln(labour) + \beta_3 \ln(inputs) + v_{it} - u_{it}$.

TABLE 3 Descriptive statistics (for Wave 1)

Variable	Mean	Std. Dev.	Min	Max	Mean difference between cash-crop and food-crop growers
Primary output is cash-crop	0.11	0.32	0	1	-
Primary output is food-crop	0.35	0.47	0	1	-
Household Commercialisation Index	48.22	7.36	0	80.40	2.12
ln(Total Food Auto-Consumed in HH)	10.75	1.21	1.78	13.94	3.05*
ln(output)	10.98	1.72	0	15.59	1.23
ln(land)	8.89	1.73	0	13.04	0.57
ln(labour)	4.26	5.30	0	16.73	0.33
ln(Other Inputs)	7.01	4.41	0	14.25	1.14*
Age of HH Head	50.09	15.10	16	110	3.02
Marital Status of HH (Married = 1)	0.75	1.71	0	1	0.22*
Religion of HH Head (Christian = 1)	0.53	0.55	0	1	0.00
Gender of HH Head	0.89	0.31	0	1	0.19*
Number of adult males in household	1.36	0.93	0	11	0.09
Number of adult females in household	1.54	0.89	0	7	0.06
Number of dependent males in household	1.69	1.62	0	16	0.13
Number of dependent females in household	1.51	1.47	0	11	0.20
Household size	6.11	3.13	1	31	1.45*
Literate (Can read and write = 1)	0.47	0.49	0	1	0.00
Years of education of HH Head	3.89	3.24	1	13	0.00
Rural	0.89	0.32	0	1	0.21
Mean per capita expenditure (MPCE) in naira	448,408.6	290,725.4	33907.57	2,975,185	243,233*

Note: * represents significance at the 5% level in the differences between the means.
Source: Authors' calculation based on the Nigerian LSMS data for 2011 and 2013.

TABLE 4 Maximum likelihood estimates of the Stochastic Frontier Analysis model with Greene (2010) correction for sample selection bias

	Coefficient	SE
Translog Production Function		
Constant	9.066	1.649
ln(*Land*)	2.363***	0.677
ln(*Labour*)	0.590	0.510
ln(*Other Inputs*)	2.220***	0.047
$\ln^2(Land)$	0.282*	0.122
$\ln^2(Labour)$	0.273***	0.086
$\ln^2(Other\ Inputs)$	0.065*	0.040
ln(*Land*) ln(*Labour*)	0.366***	0.015
ln(*Land*)ln(*Other Inputs*)	0.794***	0.014
ln(*Labour*)ln(*Other Inputs*)	0.398***	0.014
Year dummy	−0.140*	0.073
σ_S^2	2.695	0.030
γ	0.163	0.002
σ_u^2	0.232	0.180
σ_v^2	3.705	0.152
$\ln(\sigma_S^2)$	0.643***	0.019
$logit(\gamma)$	−1.133***	0.160
μ	19.387	22.131
Statistics		
No. of obs.	5192	
No. of groups	3045	
Log likelihood (Trans-log)	−987.4	
Log likelihood (Cobb–Douglas)	−1719.32	
LR-stat for $H_{o:}$ The two ratios are not different	1002.13***	
Decision	Trans-log preferred	
Elasticities and marginal products of factors of production		
Elasticities		
Land	0.390***	0.100
Labour	0.409***	0.071
Other Inputs	0.201***	0.071
Marginal partial product		
Land	223.02	22.44
Labour	14.71	1.870
Other Inputs	1.420	0.460

Notes: The result is based on Equation (3). σ_S^2 is the estimate of the sum of σ_u^2, the variance of u_{it}, the technical inefficiency error term, and σ_v^2, the variance of v_{it}, the idiosyncratic error term. γ is the estimate of σ_u^2 / σ_S^2, showing the estimated proportion of the inefficiency component in the total variance in the aggregate error term. μ is the estimate of the mean of the technical inefficiency error term, where $u_{it} \sim^{iid} N^+(\mu, \sigma_u^2)$.

Elasticities are evaluated at the geometric means of the inputs and output; Standard errors are calculated using the delta method.

***, **, * represents significance at 1%, 5%, and 10% alpha respectively.

Source: Authors' calculation based on the Nigerian LSMS data for 2011 and 2013.

In this case, β represents the parameter of interest as the average net effect of being treated on the outcomes, μ_i is the unobservable time fixed effect and v_{it} is the error term. However, since $\boldsymbol{C}_{it}$, the crop choice, is endogenous, we would need to model the selection into treatment or the farmer's crop choice following Greene (2010). Further technical details of the treatment effects model are shown in Appendix S2.

3.5 | Data

For this analysis, we use the Nigeria General Household Survey-Panel (GHS-Panel) for 2010/2011 (Wave 1) and 2012/2013 (Wave 2), which is the official comprehensive household survey for Nigeria and is part of the Living Standards Measurement Study-Integrated Surveys on Agriculture (LSMS-ISA) series from the World Bank.[7] The panel covers all the 36 states of the country, including the Federal Capital Territory, Abuja. The survey method was based on a two-stage probabilistic sampling technique to select clusters (or neighbourhoods) at the first stage and households at the second stage. Clusters were selected from each of the 36 states. Sampling was carried out on both urban and rural Enumeration Areas (EAs) and is thus nationally representative. The total number of EA is 500.

For the GHS-Panel, 5000 households were randomly surveyed out of 22,000 in the cross-sectional part. The survey for each wave was done in two stages: the post-planting period (lean season), once in 2010 and once in 2012 and the post-harvest period, once in 2011 and once in 2013. In addition, the post-planting survey includes the 22,000 cross-sectional households while the post-harvest survey includes just the 5000 households in the panel sample where 10 households were randomly selected in each of 500 EAs. Table 3 shows descriptive statistics of our variables for Wave 1.[8]

4 | RESULTS

4.1 | Agricultural productivity in Nigeria

Table 4 shows the results of the crop productivity estimation of agricultural households in Nigeria, using the SFA with Greene's (2010) correction for sample selection bias regarding the decision over whether cash or food crops are chosen. The result of the production function (based on Equation 3) shows that all the covariates, that is, the logarithms of input terms, the squared logarithms of input terms, and the cross-interactions of the logarithms of input terms are statistically significant, except ln(*Labour*). Our inputs all positively contribute to household-level agricultural output, with stronger positive effects from the squared and cross terms. For instance, a 1% increase in land leads to a 2.36% increase in output, without considering the effects from the squared- or cross-log terms. However, as the land increases, output increases more than proportionally. This will be further accelerated for a higher level of labour or inputs. That is to say, larger landholders achieve a high level of output and their productivity in terms of *economic efficiency* or *per-unit output* is greater than that of smallholders. It

[7] We have used the first two waves of the available four waves in GHS as most of the households were revisited in the second wave so the attrition bias is negligible. The use of the first two surveys would minimise the attrition bias. However, future research should use Waves 3 and 4 (in 2015/16 and 2018/19) to see if our findings remain unchanged by correcting the attrition bias.

[8] Appendix S3 provides descriptive statistics for Wave 2. Differences of the variables between cash-crop farmers and food-crop farmers and their statistical significance are shown in the last column of Table 3 and the table in Appendix S3. It should be noted that there are no significant differences in output, land or labour but cash farmers on average use a significantly larger amount of inputs and have more household members.

TABLE 5 Technical efficiencies of different segments of the population by the characteristics of the household heads (from Wave 1) based on SFA with Greene (2010) correction for sample selection bias

	Male	Female	Age (<20)	Age (20–60)	Age (>60)	Land size (<1 ha)	Land size (1–5 ha)	Land size (5–10 ha)	Land size (>10 ha)
Technical efficiency (<25%)	5%	13%	10%	1%	6%	6%	8%	7%	7%
Technical efficiency (25%–50%)	19%	37%	20%	6%	10%	19%	20%	12%	45%
Technical efficiency (50%–75%)	66%	50%	69%	69%	64%	70%	67%	67%	38%
Technical efficiency (>75%)	10%	0%	1%	24%	20%	5%	5%	14%	10%
Overall average technical efficiency	64%	60%	63%	75%	64%	64%	64%	61%	60%

Source: Authors' calculation based on the Nigerian LSMS data for 2011 and 2013.

should be noted, however, this does *not* imply a higher level of technical efficiency, denoting the extent to which the observed level of output is close to the maximum feasible output given the observed levels of land, labour and inputs.

A similar relationship is observed between labour and outputs or inputs and output. However, the estimated coefficient of ln(*Labour*) is positive and not statistically significant, while $\ln^2$(*Labour*) and cross-log terms are significant. On the other hand, the estimated coefficients of both ln(*Other Inputs*) and $\ln^2$(*Other Inputs*) are statistically significant. Overall, the results suggest that the total output increases as input levels increase proportionally.

These results show that the overall technical efficiency averages 64.3% (estimate of $\ln\left(\sigma_S^2\right)$). This is lower than existing estimates from more crop-specific studies (e.g., cassava—89% by Adeyemo et al., 2010; rice—65% in Onyenweaku & Ohajianya, 2009) or from food crops 68% (Amaza et al., 2006). Since we focus on the total output of the household, the inefficiency we observe is, perhaps, more worrying. Using the econometric results of the trans-log model and following Chen et al. (2009), we derive the elasticities and marginal products of factors of production as presented in the bottom panel of Table 4.

Table 5 shows the variation in technical efficiency across the sample by gender and age of the household head as well as household land area, based on the first wave.[9] As expected, the most 'technically efficient' age of the head of the household ranges between 20 and 60. The results of Table 5 can be associated with Schultz's (1964) hypothesis of 'the efficient small farmer'. Here, we find that technical efficiency declines as land size increases. Furthermore, most of the households with the land size below 10 hectares fall within the 50%–75% range of technical efficiency, while the share between 25% and 50% is the largest for the large landholders with the land size above 10 hectares. However, as shown above (Table 4), small-holders are 'economically inefficient' as a statistically significant coefficient estimate of $\ln^2$(*Land*) in Table 4 implies that as land size increases, the output tends to increase more than proportionally. It should be noted that, given that land size remains almost the same between the rounds, the land-output relationship primarily exhibits as a cross-sectional relationship.

4.2 | Impact of crop choice on technical efficiency and poverty

We test whether the productivity and welfare differences between the two groups of farmers with different crop choices (i.e., cash and food crops) are significantly different from zero after controlling for household characteristics and addressing the endogeneity associated with farmers' crop choice.

The results are reported in Tables 6 and 7. Column (1) of both tables shows the results of the first stage selection into the treatment equation, determining the probability of being treated (growing cash crops). However, since these are drawn from probabilistic functions and not from linear probability modelling, the coefficients cannot be interpreted as probabilities, but indicate the direction of the effect and its statistical significance. Column (2) indicates the results of the second stage impact equation, showing the average treatment effect on the treated (i.e., the households choosing cash crops) in comparison with the counterfactual (same households chose food crops rather than cash crops) given observable household characteristics and unobservable household fixed effects.

The exclusion restrictions used for the equation are: the amount of free input used in production, non-farm income and the amount of seed used in the previous growing season.

[9]We obtain similar results for the second wave. This is available in the Online Appendix.

TABLE 6 Treatment effects model results for the selection of crop equation and the impact of crop choice on technical efficiency

	C_1—Farmer chose a cash crop	
	Selection	**Impact**
	(1)	**(2)**
Crop Choice		0.026*** (0.001)
Age of HH Head	0.015 (0.990)	0.0003 (0.0006)
Age Square of HH Head	−0.055 (0.22)	−0.0000 (0.0000)
Education of HH Head	0.0007 (0.000)	−0.0433*** (0.0028)
HH Size	0.149*** (0.008)	−0.440*** (0.280)
Sex of HH Head	0.527*** (0.054)	0.857*** (0.055)
Rural	−0.004 (0.007)	0.065 (0.048)
Female Share	0.000 (0.000)	−0.000 (0.001)
Married	0.354*** (0.002)	0.000 (0.001)
Region1 (NW)	0.167 (0.209)	−0.008* (0.004)
Land Size	0.541*** (0.099)	1.793*** (0.821)
Farm Machinery owned	0.020*** (0.001)	0.002 (0.002)
Region2 (NC)	2.340*** (0.711)	0.166*** (0.004)
Region3 (SW)	−1.207*** (0.112)	−0.197 (0.187)
Region4 (SE)	2.131*** (0.209)	−0.001*** (0.000)
Region5 (SS)	2.903*** (0.901)	0.032 (0.022)
Free Inputs[a]	0.877*** (0.199)	
Non-farm income[a]	0.107* (0.067)	
Previous year's seeds[a]	0.902*** (0.081)	
Constant	−16.384*** (0.495)	7.588*** (0.018)
F-stat, excl. Instruments	29.04	
p-value	0.000	
N	2422	2422
Time Dummies	Yes	Yes

Note: Robust standard errors in parentheses.

$^{***}p<0.01$, $^{**}p<0.05$, $^{*}p<0.1$.

Source: Authors' calculation based on the Nigerian LSMS data for 2011 and 2013.

[a]Exclusion restrictions; *F*-stat below 10 indicates weak instruments.

TABLE 7 Treatment effects model results for the selection of crop equation and the impact of crop choice on poverty (log MPCE)

	C_1—Farmer chose a cash crop	
	Selection(Probit)	**Impact**
	(1)	**(2)**
Crop Choice		−0.530** (0.009)
Age of HH Head	−0.007 (0.019)	0.008 (0.007)
Age Square of HH Head	0.001 (0.00)	0.000 (0.00)
Education of HH Head	−0.055 (0.095)	0.085 (0.037)
HH Size	0.101* (0.008)	0.150*** (0.008)
Sex of HH Head	0.537*** (0.054)	−0.274** (0.096)
Rural	−0.22 (0.34)	0.011 (0.057)
Female Share	−0.00007 (0.000)	−0.029*** (0.006)
Married	0.177 (0.163)	−0.075*** (0.017)
Land Size	0.816*** (0.018)	0.065*** (0.003)
Farm Machinery owned	0.191*** (0.020)	0.191*** (0.020)
Region1 (NW)	0.560* (0.270)	−0.118* (0.052)
Region2 (NC)	1.266*** (0.257)	−0.221*** (0.056)
Region3 (SW)	1.276*** (0.289)	−0.038 (0.087)
Region4 (SE)	1.277*** (0.263)	−0.239*** (0.061)
Region5 (SS)	2.471*** (0.263)	−0.087 (0.080)
Free Inputs[a]	0.677*** (0.023)	
Previous year's seeds[a]	0.420* (0.10)	
Constant	−2.706*** (0.619)	11.084*** (0.235)
F-stat, excl. Instruments	25.02	
p-value	0.000	
N	2422	2422
Time Dummies	Yes	Yes

Note: Robust standard errors in parentheses.

*** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Source: Authors' calculation based on the Nigerian LSMS data for 2011 and 2013.

[a]Exclusion restrictions; *F*-stat below 10 indicates weak instruments.

The instruments are strong as the F statistic for excluded instruments is 29.04. For the consumption expenditure equation, only the free input[10] and previous year's seeds are used because non-farm income is directly related to household expenditure. These variables were positive and significant in determining participation in growing export-oriented (cash) crops and tubers or roots as food crops. The instruments are also strong with the F statistic for excluded instruments equal to 25.02. The positive and significant free input coefficient suggests that they act as a buffer to reduce the cost and risk of planting cash rather than food crops.

Other major significant determinants of choosing cash crops include the land size, the region in which the household resides, the size of the household and the gender of the household head. The more land a household has, the more likely it is to grow cash crops. The region effect reflects the fact that some crops grow better in some areas than others, where topological or geographic factors influence crop choice. Larger households are more likely to plant cash crops. This may be because larger households can devote more labour to cash-crop production, and/or that larger households have greater income requirements.

Our main finding is that households adopting cash crops, given the observable household characteristics and unobservable household fixed effects, have better technical efficiency by 0.026 on average than their food crop counterparts.

Table 7 indicates, however, that the selection of cash crops has a significant negative effect on the log of mean household per capita expenditure (MPCE). This implies that, if a food-crop farmer chooses to grow cash crops, the expenditure of the household headed by that farmer is likely to be lower. This would increase overall poverty by making a non-poor household poor or a poor household poorer. It should be noted that this estimate is based on the methodology taking into account sample selection bias and the current household characteristics. Even if cash crops would potentially increase productivity, unless the cash-crop producers are supported by policies that would help them grow new crops, it would not make sense for the food-crop farmers to switch to cash crops given the current conditions, as this switch would make them potentially poorer.

Finally, Tables 8 and 9 report the results of the impact of commercialisation, and its interactions with cash crop or food crop choice, on technical efficiency and poverty. In each table, Columns 1 and 2 show the results for commercialisation without any interaction terms based on a Fixed-Effects (FE) model and a Correlated Random Effects (CRE) model. On the other hand, Columns 3 and 4 show the impact of commercialising the cash crops, and Columns 5 and 6 for that of commercialising food crops. The results in Columns 1 and 2 of Table 8 show that the household index of commercialisation is not a statistically significant determinant of technical efficiency, but it is significant for poverty. This is somewhat surprising because one might expect that the more commercialised a farm household is, the better its technical efficiency would be, due to the market incentives. However, the incentives to the household head of increasing technical efficiency to keep his family fed may be greater than the incentives from doing so for the sake of the possible sale value of his goods. Our results thus suggest that food security is at least as important as commercialisation in increasing technical efficiency. The result in Columns 1 and 2 of Table 9 that commercialisation is negatively associated with MPCE implies that, if poverty alleviating policy is the main policy concern, commercialisation alone is not sufficient.

However, some interesting results emerge when the crop choice variables are interacted with the index of commercialisation. For instance, if food crops are commercialised, the technical efficiency tends to be higher (Columns 5 and 6 of Table 8), while similar results are not found

[10]The free input variable is a dummy representing whether the farmer has used any seeds, fertilisers, pesticides or other farm inputs provided for the farmer's use by either the government or a non-governmental organisation, free of cost.

TABLE 8 Results of impact of crop commercialisation with crop choice on technical efficiency: Fixed Effects (FE) model and Correlated Random Effects (CRE) model

	FE	CRE	FE	CRE	FE	CRE
	(1)	(2)	(3)	(4)	(5)	(6)
Commercialisation	0.012 (0.038)	0.018 (0.038)				
Cash crop * Commercialisation			−0.03 (0.026)	−0.112 (0.113)		
Food crop * Commercialisation					0.046* (0.203)	0.070** (0.325)
Age of HH Head	0.134*** (0.027)	0.008 (0.007)	0.096*** (0.027)	0.008 (0.007)	0.096*** (0.027)	0.008 (0.007)
Age Square of HH Head	−0.000 (0.000)	−0.000 (0.000)	−0.000 (0.000)	−0.000 (0.000)	−0.000 (0.000)	−0.000 (0.000)
Sex of HH Head	−0.022* (0.013)	−0.300** (0.096)	−0.022* (0.013)	−0.300** (0.096)	−0.022* (0.014)	−0.300** (0.096)
Education of HH Head	0.096 (0.095)	0.067 (0.037)	0.096 (0.095)	0.067 (0.037)	0.096 (0.095)	0.067 (0.037)
HH Size	0.747*** (0.045)	0.152*** (0.008)	0.747*** (0.045)	0.152*** (0.008)	0.747*** (0.045)	0.152*** (0.008)
Rural	0.01 (0.35)	0.019*** (0.01)	0.01 (0.35)	0.019*** (0.01)	0.01 (0.35)	0.019*** (0.01)
Female Share	−0.022 (0.22)	−0.050 (0.041)	−0.022 (0.22)	−0.050 (0.041)	−0.022 (0.22)	−0.050 (0.041)
Married	2.02e-05 (1.81e-05)	0.358 (0.041)	2.02e-05 (1.81e-05)	0.358 (0.041)	2.02e-05 (1.81e-05)	0.358 (0.041)
Farm Machinery owned	0.210*** (0.0270)	0.988*** (0.0178)	0.210*** (0.0270)	0.988*** (0.0178)	0.210*** (0.0270)	0.988*** (0.0178)
Land Size		0.209*** (0.0210)		0.201*** (0.0210)		0.208*** (0.0210)
Region1 (NW)		−0.808*** (0.280)		−0.808*** (0.280)		−0.808*** (0.280)

(Continues)

TABLE 8 (Continued)

	FE	CRE	FE	CRE	FE	CRE
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Region2 (NC)		0.766*** (0.316)		0.766*** (0.316)		0.766*** (0.316)
Region3 (SW)		−0.001 (0.00)		−0.001 (0.00)		−0.001 (0.00)
Region4 (SE)		−0.299 (0.270)		−0.299 (0.270)		−0.299 (0.270)
Region5 (SS)		−0.087 (0.080)		−0.087 (0.080)		−0.087 (0.080)
Constant	10.23*** (0.326)	11.095*** (0.229)	10.23*** (0.326)	11.095*** (0.229)	10.23*** (0.326)	11.095*** (0.229)
N	2422	4844	2422	4844	2422	4844
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes

Note: Robust standard errors in parentheses.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Source: Authors' calculation based on the Nigerian LSMS data for 2011 and 2013.

TABLE 9 Results of the impact of crop commercialisation with crop choice on poverty (log MPCE): Fixed Effects (FE) model and Correlated Random Effects (CRE) model

	FE	CRE	FE	CRE	FE	CRE
	(1)	(2)	(3)	(4)	(5)	(6)
Commercialisation	−0.140***	−0.060***				
	(0.026)	(0.008)				
Cash crop * Commercialisation			0.022*	0.0188***		
			(0.00766)	(0.006)		
Food crop * Commercialisation					−0.088*	−0.232***
					(−0.021)	(0.022)
Age of HH Head	0.088***	−0.001	0.088***	−0.001	0.088***	−0.001
	(0.027)	(0.003)	(0.027)	(0.003)	(0.027)	(0.003)
Age Square of HH Head	−0.000	−0.000	−0.000	−0.000	−0.000	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Sex of HH Head	−1.640	0.080***	−1.740	0.080***	−1.740	0.080***
	(1.025)	(0.015)	(1.025)	(0.015)	(1.025)	(0.015)
Education of HH Head	0.096	0.079***	0.096	0.079***	0.096	0.079***
	(0.095)	(0.004)	(0.095)	(0.004)	(0.095)	(0.004)
HH Size	0.747***	−0.004	0.747***	−0.004	0.747***	−0.004
	(0.045)	(0.044)	(0.045)	(0.044)	(0.045)	(0.044)
Rural	0.01	−0.142***	0.01	−0.142***	0.01	−0.142***
	(0.35)	(0.026)	(0.35)	(0.026)	(0.35)	(0.026)
Female Share	−0.022	0.009	−0.022	0.009	−0.022	0.009
	(0.22)	(0.008)	(0.22)	(0.008)	(0.22)	(0.008)
Married	0.00001	−0.056***	0.00001	−0.056***	0.00001	−0.056***
	(0.000)	(0.008)	(0.000)	(0.008)	(0.000)	(0.008)
Farm Machinery owned	0.779***	0.816***	0.779***	0.816***	0.779***	0.816***
	(0.0270)	(0.0178)	(0.0270)	(0.0178)	(0.0270)	(0.0178)
Land Size		0.191***		0.191***		0.191***
		(0.0210)		(0.0210)		(0.0210)

(Continues)

TABLE 9 (Continued)

	FE	CRE	FE	CRE	FE	CRE
	(1)	(2)	(3)	(4)	(5)	(6)
Region1 (NW)		−0.267***		−0.267***		−0.267***
		(0.024)		(0.024)		(0.024)
Region2 (NC)		0.060*		0.060*		0.060*
		(0.027)		(0.027)		(0.027)
Region3 (SW)		0.019		0.019		0.019
		(0.041)		(0.041)		(0.041)
Region4 (SE)		−0.159***		−0.159***		−0.159***
		(0.032)		(0.032)		(0.032)
Region5 (SS)		0.140***		0.140***		0.140***
		(0.039)		(0.039)		(0.039)
Constant	5.198***	11.095***	5.198***	11.095***	5.198***	11.095***
	(1.233)	(0.229)	(1.233)	(0.229)	(1.233)	(0.229)
N	2422	4844	2422	4844	2422	4844
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes

Note: Robust standard errors in parentheses.

*** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Source: Authors' calculation based on the Nigerian LSMS data for 2011 and 2013.

for cash crops (Columns 3 and 4). We observe in Table 9 that, if the cash crop is commercialised, MPCE tends to be higher (Columns 3 and 4), while if the food crop is commercialised, MPCE tends to be lower (Columns 5 and 6). We can speculate that the commercialisation of cash crops reduces poverty through the income generated by market sales. However, the commercialisation of food crops would reduce the self-consumption at home and could potentially make the household poorer, or food insecure. Hence, if the government adopts an agricultural policy of commercialising the agricultural products, it should pay attention to the type of crops with respect to their differential impact on household poverty.

5 | CONCLUSION

The present study examines the question of whether smallholder farmers in Nigeria experience technical efficiency and welfare differences depending on their production of cash versus food crops, and the factors which determine these farmers' crop choices. Using two rounds of LSMS panel data from Nigeria in 2010/11 and 2012/13, we revisit the arguments about whether smallholders are 'efficient but poor' (Abler & Sukhatme, 2006). We apply a stochastic frontier analysis (SFA) with Greene's (2010) correction for sample selection about crop choices. We find that smallholders are generally efficient in their allocation of resources. Access to free inputs, non-farm income, the use of seeds from the previous growing season, owned land, household size, gender and the regional differences were the main determinants of choosing to grow cash crops. The results of our SFA analysis imply that larger farmers—who typically grow cash-crops—are productive and economically efficient, though not as technically efficient as their smaller counterparts. Although there is an economic incentive to switch to cash crops, the results of our selection equation imply significant costs associated with cash crops (e.g., acquiring larger land, using more inputs). Consistent with this observation, our findings also imply that cash crop production does not reduce poverty, although it does marginally improve technical efficiency. However, poverty is reduced by commercialisation.

Our results suggest that agricultural household crop choices are not random, but can be predicted by socioeconomic factors. If the government wishes to promote cash crop production, the policies helping farmers purchase inputs at lower prices (e.g., microcredit programmes or subsidies for poor farming households) would be useful in this context. However, the government should also be aware that a switch to cash crops without adjustment of farmers' factor endowments can be poverty-increasing. Shultz's argument for investment in human capital, particularly education (Schultz, 1961) is still valid in the present context to help poor farmers invest in new technologies and escape from poverty. Agricultural extension could be utilised to get more people within areas of comparative advantage to switch to these high productivity crops to improve their welfare. Educating farmers on the marketing opportunities for their products, and concomitant greater commercialisation would also have positive welfare effects.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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