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Determinants of Food Security and Technical Efficiency among Agricultural Households in Nigeria

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Abstract: The challenge of food security in Nigeria hinges on several factors of which poor technical efficiency is key. Using a stochastic frontier framework, we estimated the technical efficiency of agricultural households in Nigeria and tested for the significance of mean technical efficiency of food-secure and food-insecure agricultural households. We further assessed the determinants of agricultural households' inefficiencies within the stochastic frontier model and adopted a standard probit model to assess the determinants of households' food security status. The results of our analyses revealed that; on the overall, the agricultural households had a mean technical efficiency of 52%, suggesting that agricultural households have the tendency of improving their technical efficiency by 48% using the available resource more efficiently. We found that households that are food-secure are more technically efficient than food in-secure households and this was significant at one-percent. Our results provide useful insights into the role of land size and number of assets as determinants of agricultural households' food security and technical efficiency status.

Keywords: food security; technical efficiency; Nigeria

JEL Classification: C01; Q12; Q18

1. Introduction

In recent times, major agricultural interventions and efforts have been geared towards increasing productivity in sub-Saharan Africa (SSA). For example, the development, dissemination, and adoption of the improved crop varieties and fertilizer technologies have been widely promoted across the region (Abdoulaye et al. 2018; Ogunniyi et al. 2015; Lunduka et al. 2017). However, low productivity still characterizes the agricultural sector in the region (FAO 2004). Apparently, interventions may be significant in increasing the level of outputs in a certain context, but such increments are prone to inefficiency, especially when the available technology is not efficiently utilized. As such, it could be argued that it is quite more cost-effective to exterminate existing inefficiency than to introduce interventions as a means of increasing agricultural households' outputs (Tefaye and Beshir 2014).

In Nigeria, agriculture is predominantly rural with diverse ecology and it remains the source of livelihood for two-thirds of the populace and contributes 40% to the Gross Domestic Product (IFAD 2012). Like in most developing countries, agriculture remains the main pathway for pro-poor development (Kassie et al. 2013; Dawson et al. 2016). It remains the source of food, income, and livelihood for most agricultural households (Dethier and Effenberger 2012). With the population in agriculture in Nigeria and the diverse resources, one may expect that agricultural households are devoid of food insecurity issues. Ironically, agricultural households are most hit by prevailing food insecurity issues despite being producers of food (Kuku-Shittu et al. 2013; Ogunniyi et al. 2016;

Ogunniyi et al. 2018). This trickles to the nation at large being the world's largest producer of cassava, cowpea, and yam, and yet food-deficit depends largely on the importation of cereals, grains, fish, and livestock products (IFAD 2012). Considerably, agricultural households' ability to produce efficiently will go a long way to meet food demands at the households' level. This is because an efficient agricultural household is more likely to be productive (Orea and Kumbhakar 2004).

In terms of technical efficiency, most of the existing literature studies focused on estimating efficiency with emphasis on a single crop and their predictors either in a single equation or using a two-step approach (see Tijani 2006; Ajayi and Olutumise 2018; Oluwatayo and Adedeji 2019). With the focus on a single crop, Tijani (2006) and Ajayi and Olutumise (2018) estimated the mean technical efficiency of rice and cassava farmers to be 86.6 percent and 83 percent, respectively in Nigeria. A first attempt to measure technical efficiencies considering multiple cropping was conducted by Ogundari (2013). The study employed a panel dataset covering three farming seasons for two periods in five South-West States (Osun, Ogun, Ekiti, Ondo, and Oyo). The results of the study revealed an increasing trend in technical efficiencies from 76.6% to 80.5%. On a wider coverage, Ogundari (2014) conducted a meta-analysis of African agricultural efficiency based on 442 frontier studies and found that the mean technical efficiency estimates decrease as the year of survey in the primary study increases. However, with a slight variation; parametric specification from panel data were quite higher, while those on grain crops were reported to have had significantly lower technical efficiency estimates.

Based on this premise, using a recent general household survey, we based our research on the reality that agricultural households in Nigeria are peasants and operate a high-risk agricultural practice, coupled with the understanding that majority of agricultural households adopt multiple cropping systems (Ajibefun et al. 2002). We further argued that there are differences in technical efficiencies of food-secure and food-insecure households, which is not explicit in previous studies. As such, predictors of technical efficiencies and food security can be quite related. We found only one study by Ajayi and Olutumise (2018) to be relevant. The study assessed the predictors of food security and technical efficiency, however in a single crop enterprise at the state level. Our approach assessed technical efficiency and food security status of agricultural households and their predictors using a recent national survey that reflects households' mixed farming enterprises. To the best of our knowledge, our research captures this objective in recent time using a national survey. Studying these factors can provide insight into limitations of technical efficiencies and food securities thereby aiding policymakers in the agricultural sector to examine and formulate national policies. Aside from this, this research is worth investigating for several reasons.

While our study is streamlined to assess the determinants of inefficiencies in multiple cropping systems, we are aware of the possibilities of exogenous activities that can impact farm-level efficiencies which are not covered in our study. For example, participation in off-farm activities was found to be significant in determining the technical efficiency of maize producers in eastern Ethiopia (Ahmed and Melesse 2018). Most farm households in developing countries engage in off-farm activities and this was found significant in driving farm efficiencies through enhancing the purchase of improved technologies (Oseni and Winters 2009; Ruben 2001). Also, households adopting various climate change adaptation practices were found to be 13% more technically efficient (Khanal et al. 2018). Beyond owning resources, social factors surrounding ownership can also be a determining factor. This is evident in Rahman and Rahman (2009)'s assessment of the impact of land fragmentation and resource ownership on productivity and efficiency among rice farmers. They found land fragmentation to be positive and significant in increasing technical inefficiencies among rice farmers in Bangladesh. Apparently, these factors can feed into predicting households' food security status as well. Empirical findings had consistently reiterated the importance of off-farm activities as stabilisers of households' production shocks which directly improve food security (Bezu et al. 2014; Babatunde and Qaim 2010; De Janvry and Sadoulet 2001). In order to statistically ascertain the presence of these omissions in our model largely due to limitations in the survey, we performed Breusch-Pagan/Cook-Weisberg test, in line with Cook and Weisberg (1983), and found our model to be heteroskedastic[1]. To partly control for this, we follow a standard procedure in line with Wooldridge (2010) by applying a robust standard error in our model. However, apart from errors that can occur from variables omission, technical efficiency frontier models may be subjected to endogeneity. There are various models and arguments about the approach to solving endogeneity (Shee and Stefanou 2015; Gronberg et al. 2015; Karakaplan and Kutlu 2017). We were however limited by data in finding suitable instrumental variables to complement for this error in our frontier model. However, this does not infer that our model is meaningless, but a means to inform national data collection to capture efficiency indicators robustly. To be quite explicit, our research objectives include the following: (i) To measure technical efficiency of agricultural households in Nigeria and assess their predictors; (ii) To test if there is significance difference in households' technical efficiency in relation to their food security status (iii) To assess the determinants of agricultural households food security status.

The rest of the paper is presented as follows: Section 2 presents the data used in this paper. Section 3 presents and discusses the empirical model used to analyse the research objectives. Section 4 presents the empirical findings and discussions. Section 5 concludes the paper.

2. Data

The data used in the study are obtained from the General Household Survey (GHS) conducted by the National Bureau of Statistics, Nigeria. The survey is conducted as part of the World Bank's Living Standard Measurement Study (LSMS) integrated surveys. Every year, a nationally representative data on agriculture, households and community level are collected in the GHS. For the purpose of the present study, we use the post-planting and post-harvest stage of wave three of the survey which collected data for the period of 2015/2016. A total of 2746 agricultural households were selected into our sample data.

The inputs variables taken from the database include geographical information estimates of land size under cultivation, labour measured in monetary terms and not man-days. Quantities of fertilizers were measured in a kilogram. Seed input variable represents different cropping systems at the households which include seeds, grains, stem cuttings, etc. Seed input variable was measured in values at the cost purchased by farmers. The crops covered in the analysis include, but not limited to cassava, maize, sorghum, yam, banana, pepper, plantain, potatoes, etc. The variable also accounted for borrowed seeds and seeds given for free at the value perceived by households as represented in the survey. Similar to Tijani (2006), our output variable was measured in value term so as to account for different local measures for different crops. We also extracted households' socioeconomic characteristics from the GHS database. These variables include the age of household head, gender, household size, number of assets, access to credit, access to fertilizer advice, and access to market advice.

We adopted a subjective measure of households' food security status based on their access to healthy and nutritious food represented in the dataset as 'unable to eat healthy and nutritious food' In the estimation, 'Yes' is coded as 1 to represent households that do not have access to healthy and nutritious food (food-insecure), while 'No' represents households that had access to healthy and nutritious food (food-secure). The use of subjective measure is increasing in economic welfare studies (for example Ravallion and Lokshin 2002; Deaton 2010 and Kassie et al. 2014).

[1] The inferential statistics based on Breusch-Pagan/Cook-Weisberg test for heteroscedasticity was used to confirm the presence of heteroscedasticity. We reject the null hypothesis (H_o) of constant variance given that *prob* > *chi2* = 0.000.

3. Empirical Approach

3.1. Technical Efficiency Model

Technical efficiency is the ability of a firm to produce maximum output given a set of inputs and production technology (Anang et al. 2016). However, differences may apply in firms' output which may fall below the maximum output known as the production frontier. Our approach obtained the inefficiencies scores of agricultural outputs through a parametric Stochastic Frontiers Analysis (SFA). Our choice of parametric SFA over the non-parametric approach hinges on its ability to account for random shocks in production activities (Aiello and Bonanno 2015). This is largely because production activities among smallholder farmers are subjected to various stochastic errors emanating from factors use.

Furthermore, our SFA model explicitly follows the cross-sectional approach detailed in Belotti et al. (2013). Our justification for adopting this approach was to minimise bias in estimation by expressing both location and scale parameter of inefficiency distribution as a function of exogenous covariates in a one-stage approach. This approach adopts the normal truncated model proposed by Wang (2002) which helps to reduce bias compared to the two-stage approach. Since our data is nationally representative and comprises different weights across regions in the country, the stochastic frontier cross-sectional approach is efficient in maximising our data characteristics.

In addition, it uses estimations of normal-gamma models via simulated maximum likelihood which provides a more flexible parametrization of the inefficiency distribution in the stochastic frontier model (Greene 2003). Further to this, the use of production function is key in a stochastic frontier analysis. We considered the simplicity of the Cobb Douglass approach and its popularity in estimating frontier models, although with the understanding of its restrictive assumption of constant elasticity and return to scale and assumption of a unit elasticity of substitution (Coelli et al. 1998). Having established our justification for this approach, we model agricultural households in our data to follow the stochastic frontier cross-sectional approach as follows:

$$y_i = \alpha + x'\beta + \varepsilon_i \tag{1}$$

$$\varepsilon_i = v_i - u_i \tag{2}$$

$$v_i \sim \mathcal{N}\left(0,\ \sigma_v^2\right) \tag{3}$$

$$u_i \sim \mathcal{F} \tag{4}$$

Modelling this to our data, y_i represents the logarithm of the value of output of the ith agricultural household, x' is a vector of the logarithm of quantities of fertilizer, hired labour and land. β represents the vector of technology parameters. While ε_i represents the composed error, v_i represents the measurement and specification error, and u_i is the inefficiency term. It is assumed that u_i and v_i are independent of each other and are identically distributed across observations in the data. Also, the inefficiency term of agricultural households follows the distribution $\mathcal{F}$. For this to be estimable, we adopted the truncated normal approach in our model (Stevenson 1980; Wang 2002) fitted by the maximum likelihood approach. Our modelled stochastic frontier analysis followed a two-step approach: first, we estimated the model parameters ∂ through maximization of the loglikelihood function $\ell(\partial)$ where $\partial = (\alpha,\ \beta',\ \sigma_u^2\ \sigma_v^2)'$. Within this stage, we obtained the point estimates of inefficiency through the mean of conditional distribution:

$$\{(u_i \middle| \hat{\varepsilon}_i),\ \text{where } \hat{\varepsilon}_i = y_i - x'\hat{\beta} \tag{5}$$

At this point, we computed technical efficiency estimates of agricultural households by disentangling the computed unobserved component from the compounded error. We followed Battese and Coelli (1995) approach to compute point estimates û of inefficiencies by using the mean

$\mathbb{E}(u|\hat{\varepsilon}_i)$ of this conditional distribution. Thus, the estimates of technical efficiency were derived as follows:

$$Technical\ Efficiency\ (\epsilon) = \exp(-\hat{u}), \tag{6}$$

where $\hat{u} = \mathbb{E}(u|\hat{\varepsilon}_i)$.

Our approach to estimating likelihood function was based on the assumption that the components of the composite error v_i and u_i are independent. The likelihood function is modelled as the probability densities of these two components, and thus we represent the log-likelihood for a sample of agricultural households as follows:

$$\ell(\partial) = \sum_{i=1}^{n} \log f_{\varepsilon}\ (\varepsilon_i|\partial) \tag{7}$$

The determinants of agricultural households' inefficiencies were modelled as follows:

$$\hat{u} = \delta_0 + \delta Z' + \theta, \tag{8}$$

where Z' represents the vector of agricultural household head age, gender, household size, credit access, number of assets, and access to advice on the use of fertilizer and market advice.

3.2. Test of Mean Difference

Similar to Oyakhilomen Oyinbo and Zibah (2015), we employed a paired sample t-test to determine if there is a significant difference between the mean technical efficiency of food-secure and food-insecure households.

3.3. Probit Model for Determinants of Food Security

The complex nature of agriculture in developing countries makes the choice of farm inputs combinations a rigorous deliberation in everyday farming activities. Most times, these choices are influenced by a range of factors that are interwoven, and as such determine farmer's status on the production frontier. Whether these factors affect food security status of agricultural households is cogent in our research. In this section, we focused on modelling the determinants of agricultural households' food security status using a binary probit model.

As illustrated in Cameron and Trivedi (2010), we distinguished between binary outcomes of y which represents the food security status of households (1 = food-insecure; 0 = food-secure). Given the latent variable, the model is defined as follows:

$$P_r(y=1) = P_r\ (Z'\beta + \mu > 0) \tag{9}$$

$$= P_r\ (-\mu < Z'\beta) \tag{10}$$

$$= F(Z'\beta) \tag{11}$$

where F is the cumulative density function specified for a standard normally distributed error term. Z' represents explanatory variables which include households' inefficiency. This was necessary to examine the effect of households' efficiency on food security to ascertain beyond the two-way t-test measure of mean technical efficiency.

4. Results and Discussion

4.1. Descriptive Statistics of Variables

The descriptive statistics of all the variables used in the model are presented in Table 1. The average value of harvest among agricultural households is NGN198,258.3, however, food-secure households significantly earned 31.06% more in harvest than food insecure households. The mean difference of land size variable between the food secure and food insecure agricultural households is found to be significant at 1%. Food secure households owned land size above the overall average, however, spent lesser on seed purchase compared to food-insecure households. Although this seed value in the analysis was not significant, there is a difference in mean cost. The mean hired labour cost incurred by food secure households is approximately 45% higher than that of food-insecure households. This difference is significant at 1%. While nearly 81.1% of households' heads are male, their mean age is about 53 years which signifies that agricultural farming households in the sample are male dominant and still in their active age. This result is similar to the findings reported by Balogun and Akinyemi (2017) and Ajayi and Olutumise (2018). On the average, agricultural households size measured by the count of all members inclusive of the household head is about eight, which clearly indicates a large household and possible a plus for family labour use in farmlands. This finding is in line with Balogun and Akinyemi (2017). While household size can be a source of family labour use, it can either impact technical efficiency positively or negatively. On the negative aspect, Tan et al. (2010) and Balogun and Akinyemi (2017) argued that large household size indicates an increase in land fragmentation among household members which could be a source of technical inefficiency. In terms of food insecurity, household size can be a predictor of food insecurity status since it reveals the burden households face to feed its members. Household size positively influences food insecurity according to some studies (Mango et al. 2014; Ahmed et al. 2017; Adepoju and Oyegoke 2018). To corroborate this, we found differences in household size between food-secure and food-insecure households to be significant at 10%. The descriptive analysis also showed that there is significant mean difference in number of assets between food secure and food-insecure households. Food secured households had an average of 16.53 assets against 14.34 for food-insecure households and above the overall average of 15.41. It is important to note that asset ownership is an indicator of wealth status and could be a driving factor of farm technology adoption which is capable a of influencing households' efficiency level. This means that wealthier households could afford costlier technologies. As argued by (Abdoulaye et al. 2018), wealth status of farmers play significant roles in the adoption of farm technology in most developing countries. As a result, it is expected that food-secure households with a high number of assets are likely to be more technically efficient.

Table 1. Descriptive Statistics of Agricultural Households.

	Full Sample	Food-Secure Households (48.9%)	Food-Insecure Households (51.1%)	Mean Difference
Value of harvest (NGN)	198,258.30 (355,514.40)	235,766.30 (403,398.9)	162,523.30 (298,752.20)	5.42 *
Seeds (value)	3329.932 (14,335.63)	3154.98 (17,966.18)	3498.16 (9716.43)	−0.62
Land size (sqm)	8748.473 (13,453.43)	10,201.73 (14,371.31)	7373.85 (14,371.31)	5.52 *
Fertilizer (kg)	846.74 (1437.92)	797.709 (1173.961)	890.223 (1645.68)	1.82
Hired labour	162,620.30 (76,014.10)	211,089.70 (895,955.70)	116,181 (614,726.20)	3.24 *
Age of household head	52.88 (14.41)	51.93 (14.12)	53.80 (14.64)	−3.40
Gender of household head	0.811 (0.39)	0.83 (0.37)	0.80 (0.41)	2.71
Household size	7.76 (3.52)	7.88 (3.55)	7.67 (3.49)	1.55 ***
Number of assets	15.41 (11.02)	16.53 (12.13)	14.34 (9.74)	5.22 *

Table 1. *Cont.*

	Full Sample	Food-Secure Households (48.9%)	Food-Insecure Households (51.1%)	Mean Difference
Credit access	0.01 (0.11)	0.013 (0.12)	0.01 (0.10)	1.03
Access to fertilizer advice	0.09 (0.28)	0.08 (0.27)	0.10 (0.30)	−1.82 ***
Access to seed advice	0.08 (0.27)	0.08 (0.27)	0.08 (0.27)	0.41
Access to marketing and sales advice	0.032 (0.18)	0.03 (0.16)	0.04 (0.12)	−2.27 **
No of observation	2746	1346	1400	

*, **, and *** indicate statistical significance at the 1%, 5% and 10% levels respectively. Standard deviation values are in parenthesis. The current official exchange rate was US$ 1 = 363.88 Naira on average in the study year.

On the overall, only 1.1% had access to credit signifying poor access to credit among agricultural households. In addition, access to fertilizer, seed and marketing advice is poor on the overall average at 8.7%, 7.9, and 3.2% respectively. There are significant differences at 10% and 5% among food secure and food insecure households who had access to fertilizer and marketing advice respectively. These results revealed poor extension services among agricultural households which may likely have an impact on their technical efficiency and food security status.

4.2. Determinants of Technical Inefficiencies of Agricultural Households

Having established the structure of agricultural households in our data, Table 2 is the output of agricultural households' frontier and inefficiency model. From the frontier model, we found all inputs to be positive and significant at 1%. In specific, land size contributed highest (0.400) to households' harvest at 1% level of significance. This result suggests that larger farms are more productive than smaller farms. While our finding agrees with Baruwa and Oke (2012), Ogundari (2014) and Alene and Hassan (2003), opposite finding such as in Ugbagbe et al. (2017) revealed an inverse relationship between farm size and output. In Ugbagbe et al. (2017), land size was negatively significant to the output of soybean in Kano State and the reason was attributed to overutilization of plant arising from excess plant population per unit area. Hired labour variable was significantly valuable in contributing to households' harvest. From the result, a 10% increase in hired labour would result in about a 2.4% increase in harvest. This finding is in line with Ugbagbe et al. (2017). A similar relationship was found in Household size which was quite significant in reducing agricultural farm households' technical efficiencies, a household with larger household size was more technically efficient. In a most developing agricultural context, household size is suggestive of labour availability for farm activities. This result suggests the importance of both hired and family labour in reducing technical efficiency. The significance of seed variable at 1% and its contribution to households' harvest may reflect various seed technology in use. This result is in line with the finding of Aldana et al. (2012). Of all the inputs, fertilizer use contributed lowest to the households' harvest. Although fertilizer use variable is significant at one percent, its elasticity is low relative to other inputs. This may reflect a possible weakness in fertilizer technology adoption among agricultural households in Nigeria. This result is in contrast with Mushunje and Belete (2001) who reported that Zimbabwean small scale communal farmers are utilising the fertilizer resource more efficiently than other factors of production.

The determinants of the inefficiency model are reported in the second part of Table 2. Negative coefficients translate to a reduction in inefficiency. We found only credit access and household size significant at 10%. The coefficient of household size was negative signifying that an increase in household size would result in a reduction in technical inefficiency. This result further reiterates the importance of household size, especially for family labour use in agriculture in Nigeria. Similarly, the coefficient of access to credit was negative, suggesting that agricultural households that have access to credit facilities reduce technical inefficiency. This result is consistent with Oyakhilomen Oyinbo and Zibah (2015) who found a negative relationship between technical inefficiency and access to credit by poultry farmers in Nigeria. Similarly, Abdulai and Abdulai (2016) and Ng'ombe and Kalinda (2015) reported that access to credit inputs has a negative relationship with technical efficiency among maize farmers in Zambia.

Table 2. Stochastic Frontier Parameter Estimates of Technical Inefficiency.

Value of Harvest(log)	Coefficients	Robust Standard Error	Z-Values
(A) Production factors			
Ln seed	0.182 ***	0.026	6.93
Ln land size	0.400 ***	0.018	21.81
Ln hired labour	0.245 ***	0.0354	6.93
Ln fertilizer	0.052 ***	0.012	4.22
Constant	6.711	0.287	23.46
(B) Inefficiency effects			
Age of household head	2.458	2.099	1.17
Gender of household head	−1.765	1.355	−1.30
Credit access	8.904 *	5.329	1.67
Fertilizer advice	−20.721	19.011	−1.09
Market advice	−14.243	14.068	−1.01
Number of assets	−0.783	0.726	−1.08
Household Size	−3.006 *	1.728	−1.74
constant	−10.226	10.487	−0.98
Usigma			
Constant	2.182 ***	0.654	3.34
vsigma			
Constant	−0.291 ***	0.061	−4.73
Sigma u	2.977 ***	0.974	3.06
Sigma v	0.865 ***	0.027	32.55
lambda	3.443 ***	0.966	3.56
Number of observations = 2746, Wald chi2(4) = 703.01, *Prob > chi2* = 0.000, Log likelihood = −4187.372			

* and *** indicate statistical significance at the 10% and 1% levels respectively.

Turning to statistically insignificant variables, the coefficient of age of household head is positive revealing that agricultural households' heads become less efficient as they grow older. This may be due to their inability to assimilate or use new technology in farming techniques. This also proposes that there is a likelihood of younger farming household to utilize farm technology better. The coefficient of the gender of household head was negative, suggesting that male households' heads were more technically efficient than female households' heads. Coefficients of fertilizer advice and market advice proved relatively important in reducing agricultural households' inefficiencies, suggesting that households with access to fertilizer and marketing advice were more technically efficient.

While Table 3 reports the overall mean technical efficiency of agricultural households and the mean technical efficiencies of food-secure and food-insecure households, Figure 1 illustrates the graphical representation of the spread of households' technical efficiency scores. The overall mean technical efficiency of agricultural households is 52% revealing that agricultural households are still largely inefficient. This result is in the range of mean efficiency result of meta-analysis technical efficiency in Africa, however, lower than 71% reported for West Africa as a whole (Ogundari 2014) and 80.1% reported by Aye and Mungatana (2011) for maize farmers in Nigeria. Our estimate is also in the same range with technical efficiency mean score reported in Wongnaa and Awunyo-Vitor (2018) and Chiona et al. (2014) for maize farmers across different ecological zones in Ghana and the Central Province in Zambia, respectively. As reported by Alene and Hassan (2003), our study was found to be lower compared to Ethiopian maize farmers that adopted improved technology (76%).

Table 3. Mean Technical Efficiency (MTE) of Agricultural Households.

Variable	Observation	Mean	Standard Deviation	Minimum	Maximum
Overall	2746	0.521	0.191	0.004	0.877
Food secure	1346	0.539	0.179	0.004	0.880
Food-insecure	1400	0.504	0.200	0.0050	0.864

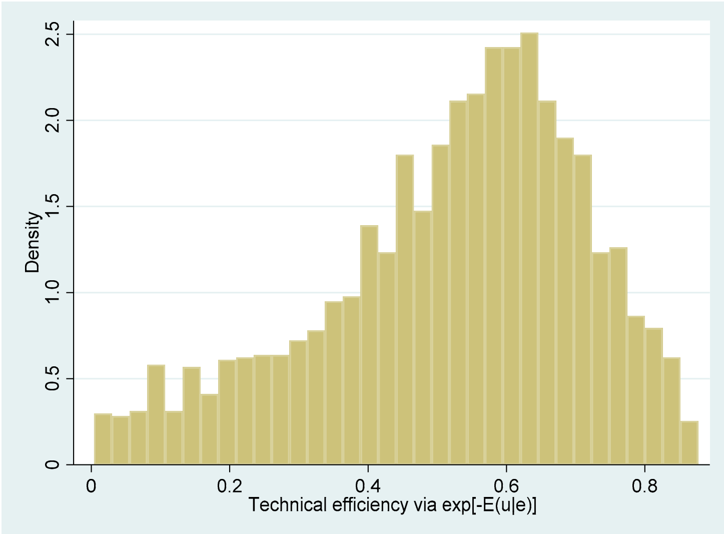

Figure 1. Graph of Agricultural Households Technical Efficiency Scores.

In addition to this finding, the mean technical efficiency scores of food-secure and food-insecure households were approximately 54% and 50% respectively. Like other results in West Africa and Africa as a whole, our estimates of technical efficiency revealed that there is much room to increase agricultural households' outputs if households can use input variables in a more efficient manner.

4.3. Mean Difference in Technical Efficiency of Food Secure and Food-Insecure Households

Table 4 presents the results of two-sample t-test of the mean difference of food-secure and food-insecure households. The result reveals food-secure households are more technically efficient than food-insecure households. The result also shows that difference between the mean technical efficiency of food secure and food insecure households are statistically significant. This suggests that technical efficiency has a likely impact on agricultural households' food security status.

Table 4. Two-sample t-test of Mean Difference of Food secure and food insecure agricultural households.

Variable	Observation	Mean	Std. Error
Food secure	1346	0.539	0.005
Food-insecure	1400	0.504	0.005
Mean Difference		0.035 ***	0.007
	t-statistics = 4.784		

*** denotes significant at 1%.

4.4. Probit Estimation of Determinants of Agricultural Households' Food Security Status

Table 5 illustrates the result of the determinants of agricultural households food insecurity status. From the standard probit estimation, all explanatory variables except credit access were significant factors driving food insecurity status of agricultural households. Age of household head was positively significant at 5% implying that younger farm household heads are more food-secured. This also points out that as households head grow older, their probability of being food-insecure is higher. A similar finding was found in (Ajayi and Olutumise 2018). In addition to this, larger agricultural household size has a higher probability of being food insecure, this was significant at 1%.

Table 5. Probit Estimation of Agricultural Households' Food Insecurity Status.

Variables	Coef.	Std. Err.	Marginal Effects
Age of Household Heads	0.004 **	0.002	0.002
Male Household Heads	0.106	0.064	0.040
Household Size	0.031 ***	0.008	0.012
Credit access	0.291	0.234	0.111
Fertilizer Advice	−0.414 ***	0.097	−0.158
Number of Assets	−0.015 ***	0.002	−0.006
Land Size (log)	−0.167 ***	0.018	−0.064
Households' efficiency	−0.691 ***	0.148	−0.263
Constant	1.650	0.528	-
Dependent variable (Unable to eat healthy and nutritious food): Food-insecure = 1, Food secure = 0			

** and *** indicate statistical significance at the 5% and 1% levels respectively.

On the other hand, the result further revealed that households' wealth status in the form of land size and number of assets owned are significant factors driving food security. Apparently, wealthier households can purchase crop produce for household needs during the lean season. Also, households with larger land size tend to have a large market base, belong to stronger membership or groups and are likely to have stronger financial support and access. Apparently, households' efficiency status was negatively significant to food insecurity implying that households that are technically efficient have reduced probability of being food insecure. This further confirms the statistically significant mean difference of technical efficiency estimates of food-secure and food-insecure households illustrated in Table 4. The role of advice on the use of fertilizer was significant at 1% with a higher coefficient, implying the need for effective extension practices that promote efficient use of fertilizer.

5. Conclusions

In Nigeria, where food security issues prevail with evidence of high production risk; high hopes on technological interventions to improve agricultural outputs is partly faced with lingering inefficiency issues. This article contributes to measuring the magnitude of technical efficiency and assessing predictors of technical efficiency and food security using data from nationally representative households and plot-level survey. While we applied the stochastic frontier model to measure technical efficiency and predictors of inefficiency in one model, we adopted a standard probit model to assess the predictors of food security. We further tested for the mean difference of technical efficiency status of food-secure and food-insecure household using a two-sample *t*-test.

We found evidence of the need for agricultural households to improve their technical efficiency by 48%. From the subjective measure of food security, we found almost half of our selected sample to be food insecure (51.1%). We found the mean difference of the technical efficiency between food secure and food insecure households to be 0.035 which is significant at 1%. This suggests that food-secure households are more technically efficient.

From the assessment of determinants of technical efficiency and food security, we found common predictors relevant to typical wealth status of rural farm households, these include land size and number of assets. This is suggestive of wealthier households' probable stronger socioeconomic characteristics which have helped them to be more technically efficient and food-secured.

Our study is based on plot-level data for a single wave of the general household survey, as a result, we are not able to capture heterogeneity effects and variability of households' food security shocks and technical efficiency. Also, there are improved frameworks on efficiency analysis, especially capturing endogenous factors, which are likely in Nigeria; a highly diverse agricultural and ecological environment. We suggest that future analysis may need to control endogenous farm factors to provide more robust evidence of the determinants of food security and technical efficiency and to see if this persists over time.

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