

# Efficiency and Its Determinants Among Smallholder Farming Units Supplying Cassava to Commercial Starch Processors in Nigeria: Data Envelopment Analysis Approach

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## Abstract

Understanding the resource allocation and use efficiency is essential considering the supportive role of agriculture in the advancement of other productive sectors of the economy. Technical efficiency and its determinants were investigated among smallholder cassava-farming and decision-taking units selected from eight states of the southeast and southwest zones of Nigeria. The states' selection was purposive, being the states in which the IITA-Nestlé cassava starch project was implemented from 2011-2015. However, a multi-stage random sampling technique was used to select a sample of 96 farming units from the clusters established under the project's out-growers' scheme. Primary data were collected from the farming units' heads by administering the pre-tested household survey instrument. Data were analysed using descriptive statistics, inferential statistics, data envelopment analysis, and multivariate ordinary least square regression techniques. The DEA results revealed that majority (73.9%) of the farming units had efficiency scores less than 1 and as such classified as inefficient. Over 30.2% of the cassava farming units had efficient scores greater than 0.8 including 3.1% with scores that ranged from 0.81- 0.99. Farming units with efficiency scores from 0.6-0.8 constituted 17.7% of the sample while those with scores from 0.4-0.6 consist of 33.3%, which also corresponds to the percentage of farming units with efficiencies scores of less than 0.5. Only three variables: cassava farming experience, fertilizer use and quantity of stems used were statistically significant ( $p < 0.05$ ) in explaining cassava farming efficiency. Of these the influence of farming experience was positive while that of fertilizer use and stems were negative. The finding suggests that the elderly and better experienced farmers combined their versatile previous knowledge of farming with willingness to adopt and use improved farming practices to achieve efficiency. Contrary to expectation, fertilizer and stems were associated with less efficiency, a surprising result that could have resulted from misapplication and wastage of the vital resources. The results highlight the need for appropriate training and technical backstopping for the heads of farming units to enhance their knowledge of the good agricultural practices and improve their levels of efficiency.

**Keywords:** DEA; best farming practices; efficiency; processing; cassava value chain; Nigeria.

## 1. Introduction

Agricultural productivity is the ratio of the total agricultural output to total inputs used in farm production (Shafi, 1984). Other things equal, it is a measure of efficiency of inputs' use (Dharmasiri, 2012). Three types of economic models for evaluating agricultural productivity have been identified as the use growth accounting technique, econometric estimation of production relationships, and the nonparametric models (Dharmasiri, 2012). Machek and Špička (2014) affirmed that each method has its advantages and disadvantages. The first is the growth accounting approach that compiles and aggregates the detailed accounts of inputs and outputs into input

and output indexes aiding the calculation of the coefficient total factor productivity (TFP). Its use imposes strong assumptions about the technology, but its major disadvantage is that its reliability cannot be evaluated using the statistical methods.

The second is the parametric approach involving an econometric estimation of production relationships either based on the production, cost or profit function (examples are found in Ike and Inoni, 2006; Bifarin et al., 2010; Enwerem and Ohajianya, 2013; Oguntari, 2010). The advantage of the approach is that it aids the quantifying of the marginal contribution of each input to the aggregate production, and also imposes fewer restrictive assumptions about technology. The average product (AP), marginal product (MP), marginal rate of technical substitution (MRTS), elasticity of production (EP), and marginal returns to scale, are among the basic concepts that assist in understanding the three production stages involved in productivity measurement and analysis (Obasi et al., 2016). Relating to the functional forms, the Cobb Douglas production function is variously used because of its straightforwardness and plasticity, although the linear, semi-log, exponential, quadratic and square root polynomials functional forms are at times used. The use of the econometric model, like the Cobb-Douglas production function, permits for the testing of hypothesis and calculation of confidence intervals needed to assess the reliability of the estimations (Dharmasiri, 2012), but the key drawback is they require use of large data. The third is the nonparametric approach, which uses linear programming techniques to calculate the TFP. It has an advantage of not imposing restrictive assumptions on the production technology, although like the growth accounting model, the fact that it cannot be statistically tested or validated is its foremost shortcoming.

Investigating agricultural efficiency is essential when considering the supportive role agriculture plays in the evolution and advancement of other productive sectors of the economy. According to Darku et al. (2013, page 1) “agricultural efficiency is a key contributor to agricultural productivity growth and efficient allocation of resources in the economy.” The authors believe that because the agrarian sector provides “productive resources” to other segments of the national economy, improving agricultural efficiency would impact positively on all other sectors (Darku et al., 2013). Consequently, in this study, an investigation was conducted on the efficiency of the smallholder farmers enlisted into a cassava value chain project implemented in some cassava-growing areas to supply cassava to major starch processors in Nigeria. The general objective of the investigation is to analyse the efficiency of cassava farming and its determinants among the smallholders. The specific objectives are to: a) examine the socio-economic individualities of the respondent cassava farmers; b) compute the efficiency index for each farming unit; and c) investigate the factors that influence efficiency of the farming units in the area. The emerging conclusions are expected to serve as an enviable policy apparatus for government’s agricultural ministries, departments and agencies (MDAs). They will also assist extension personnel, development agencies and partners, non-governmental organizations (NGOs), community development organizations (CDOs), and other stakeholders in their cassava value chain development works.

## 2. Literature review

Evidence from literature shows that there had been concerted efforts at investigating the efficiency of different agribusiness value chains across the globe (including Rodriguez-Alvarez et al., 2007; Coelli et al., 2002; Fan, 1999; Ali and Byerlee, 1991). The developing economies in general and Nigeria in particular are by no means exception to this regard (examples include Chepng’etich et al., 2014; Ambali et al., 2012; Baruwa and Oke, 2012; Adeyemo et al., 2010; Okoruwa et al., 2009; Ike and Inoni, 2006; Akinwunmi and Djato, 1997; 1996). The uniqueness of most of the studies is their common understanding and definition of a technically efficient farmer to be one located on the frontier, as against an inefficient farmer located farther away (Okoruwa et al., 2009; Greene, 2007; Coelli et al., 2002). The works reviewed in this study are restricted to those conducted across different crops value chains during the last decade (i.e. from 2006-2018).

The use of the stochastic frontier production function that incorporated a model of inefficiency was demonstrated in the investigation of the determinants of yam production in southeast Nigeria (Ike and Inoni, 2006). Labour and material inputs were identified as the major factors influencing changes in yam output while some farmer-specific variables like education, farming experience, and access to credit had significant influence on the observed variations in inefficiency among yam producers. The same approach was used to analyze the small-scale cocoyam production in Ondo State, southwest Nigeria (Baruwa and Oke, 2012). Results indicated that the technical efficiencies of the farmers were fairly high with a mean of 84.3%. Among the socio-economic variables, only education had a significant positive influence on production efficiency while the influence of household size, off-farm income, access to credit, and farming experience was negative. Other studies that applied the different aspects of the econometric modelling<sup>1</sup> include an investigation of the integrated food crops production in Oyo State, Nigeria (Fasasi, 2007), assessment of the technical, allocative and economic efficiencies of plantain (*Musa* spp.) farmers in Ondo State (Bifarin et al., 2010), pond fish production in Delta State, Nigeria (Inoni, 2007), and pepper (*Capsicum* spp.) production among selected farmers in north-western Nigeria (Adeoye et al., 2014).

Also, Enwerem and Ohajianya (2013) examined the technical efficiency and the sources of inefficiency in

large- and small-scale rice production in Imo State, Nigeria. Results of the study showed that the mean technical efficiency indexes were 0.65 and 0.69 for large- and small scale-farmers respectively. It identified low capital base for investment, poor extension contact, and poor access to credit as major factors that influenced the farmers' level of technical efficiency. In another study that compared the relative economic efficiency of small and large rice farms in the central Nigeria, Okoruwa et al. (2009) applied the profit function approach and found that improved seed, fertilizer, capital, and gender of respondents significantly affected economic efficiency. They also observed existence of significant difference in economic efficiency between small and large farms. On cassava, Asogwa et al. (2006) investigated the farmers in Benue State, north-central Nigeria and found that annual farm income, processing cost, gross margin, farming experience, education and extension contact significantly affected their technical efficiency. They recommended use of policy measures that would guarantee increase in farm income and gross margin, cost-effective improved cassava processing technology, increased access to quality education and extension services, and adequate enabling environment to attract experienced farmers into the cassava industry to enhance technical efficiency in cassava production. Similarly, Adeyemo et al. (2010) estimated the economic efficiency of small-scale cassava growers in Ogun State, Nigeria, and revealed that percentage efficiency ranged from 88.69–100 with a mean of 89.4. They concluded that whereas the costs of fertilizer and herbicides, membership of cooperatives, and levels of education enhanced technical efficiency, farmers' age and farming experience boosted the technical inefficiency of the farmers.

Among the numerous studies that demonstrated the use of the nonparametric approach of DEA are Iduma et al. (2016), Popoola et al. (2015), Okeke et al. (2012) and Asogwa et al. (2011), An investigation that used a combination of the DEA and OLS regression techniques to assess the technical efficiency (TE) of food crop farmers in River state, Nigeria, found that majority of the farmers were not technically efficient, although the mean efficiency index was 0.94 (Iduma et al., 2016). The OLS results found further that gender had a significant positive effect on TE, but membership of association had a significant negative effect. Also, Popoola et al. (2015) studied the profitability, technical efficiency and drivers of efficiency among cocoa farmers in southwest Nigeria, using the gross margin analysis, DEA and the OLS regression techniques. Among other things they found that the cocoa value chain enterprise was profitable, but the returns varied among the three evaluated states of Ekiti, Ondo and Osun. The majority of cocoa farmers were relatively technically efficient in their use of resources, with a mean technical efficiency of 0.8126. Farmers in Ekiti state were most technically efficient with a mean index of 0.8922 followed by Ondo state farmers with a mean of 0.8132 while Osun state farmers with the least mean of 0.7323.

Okeke et al. (2012) analyzed the technical and scale efficiencies for irrigated and rain-fed rice farmers in Anambra State, Nigeria, using data envelopment analysis (DEA). They found that the irrigated rice farmers were more efficient in the use of resources. Also, they found there was need for a significant scope of reduction in input usage while maintaining the same output levels. Applying the “cost approach constant returns to scale and variable returns to scale” DEA models, Asogwa et al. (2011) appraised the farm resource management of the rural farmers in Benue State, Nigeria. Among other revelations, the study found that scale efficiency varied substantially among the farming units with a mean scale efficiency of 0.70. They affirmed that the decision-making units operated at different levels of the optimal scale, a condition they attributed to the low level of overall “economic efficiency,” higher cost or “allocative inefficiency” and “scale inefficiency” (operating at less than optimal scale size).

### 3. Methodology of research

#### 3.1. Study area

The study was conducted in the eight states in which the cassava starch value chain project supported by Nestlé Nigeria Plc was implemented from 2011-2015 by the International Institute of Tropical Agriculture (IITA), Ibadan, Nigeria. The project area was partitioned into two: the south-east project axis (SEPA) with 5 states and the south-west project axis (SWPA) with 3 states. The communities/villages that participated in the programme were selected to fall within 150 kilometer radius around the starch factories (Matna Foods Company Limited, Ogbese, Ondo State and the Nigerian Starch Mills Limited, Uli, Anambra State) to which the farming units supply cassava under the project.

Abia state – SEPA with headquarter at Umuahia, located at latitude 5.417°N and longitude 7.500°E, land area of 6,320 sq. km, population of 2,845,380 (50.27% male), 17 local government areas (LGAs), and an average annual rainfall range for May-October of 1,600 mm – above 1,800 mm, 1981-2015.

Anambra state – SEPA with headquarter at Awka, located at latitude 6.333°N and longitude 7.000°E, land area of 4,844 sq. km, population of 4,177,828 (50.70% male), 21 LGAs, and an average rainfall annual range for May-October of 1,400 mm – above 1800 mm, 1981-2015;

Delta state – SEPA with headquarter at Asaba, located at latitude 6.2000°N and longitude 6.7300°E, land area of 17,698 sq. km, population of 4,112,455 (50.32% male), 25 LGAs, and an average annual rainfall range for May-October of 1,400 mm – above 1800 mm, 1981-2015;

Enugu state – SEPA with headquarter at Enugu, located at latitude 6.5000°N and longitude 7.500°E, land area of 7,161 sq. km, population of 3,267,837 (48.84% male), 17 LGAs, and an average annual rainfall range for May-October of between 1201 mm – 1400 mm, 1981-2015.

Imo state – with headquarters at Owerri, located at latitude 5.480°N and longitude 7.030°E, land area of 5,100 sq. km, population of 3,927,563 (50.32% male), 27 LGAs, and average annual rainfall range for May-October of 1,601 mm – above 1,800 mm, 1981-2015.

Ekiti state – SWPA with headquarters at Ado-Ekiti, located at latitude 7.620°N and longitude 5.220°E, land area of 6,353 sq. km, population of 2,398,957 (50.67% male), 16 LGAs, and an average annual rainfall range for May-October of 1,001 mm – 1,400 mm, 1981-2015.

Ondo state – SWPA with headquarters at Akure, located at latitude 7.250°N and longitude 5.190°E, land area of 15,500 sq. km, population of 3,460,877 (50.42% male), 18 LGAs, and an average annual rainfall range for May-October of 1,001 mm – 1,400 mm, 1981-2015.

Osun state – SWPA with headquarters at Osogbo, located at latitude 7.750°N and longitude 4.561°E land area of 9,251 sq. km, population of 3,416,959 (male is 50.75%), 30 LGAs, and an average annual rainfall range for May-October of 1,001 mm – 1,400 mm, 1981-2015.

Among other things, the states are endowed with fertile lands that are conducive for annual production of food and cash crops. Food security crops like yams, cocoyam, plantain and banana, cassava, maize, sweet potatoes and melon are common among the produce from the area. At least one or more of the states also produce cash crops like cocoa, kolanuts, cotton, coconuts and palm produce. Furthermore, most of the states have natural resources like rivers and lakes, coal, lead, limestone, zinc, and crude petroleum resources. Like other southern Nigerian states, the eight states have minimum average annual rainfall range of 1,000-1,800 millimeters between May and October. According to FEWS Net (2016), the rainfall trends and patterns in southern Nigeria have been stable for over 35 years, 1981-2015.

### 3.2 Study sample and data selection

The eight states in which the study was carried out were the states in which the IITA-Nestlé Nigeria cassava value chain project was implemented. A multi-stage random sampling technique was used to select the sample among the cassava farming units from the numerous clusters established under the project. A cluster was made up of 10-20 members and three clusters were selected from each state. Thereafter, four farming units were randomly selected from each of the three clusters in the second stage to give rise to 96 farming units. The survey instrument (pre-tested structured household questionnaire) used for the study was administered to the selected farming units to generate the primary data. Data collected from farming units on the yield were confirmed by an on-farm yield sampling of 0.2% of each sampled farmer's cassava farm on a 4 m x 5 m spacing basis and the yield extrapolated for one-hectare (100 m x 100 m) equivalent. Information was also collected on the head of farming units' demographics, size and charges of inputs, together with workers, soil nourishment, stalk shaping, herbicides, and produce volume and prices.

### 3.3 Methods of data analysis

Data were analyzed using descriptive and inferential statistics, the data envelopment analysis (DEA) of efficiency, and multivariate ordinary least square regression techniques. The “descriptive and inferential statistics” involve use of averages, frequencies and percentages, standard deviation, coefficients and statistics that summarize information on variables. Statistical tests were also conducted where necessary and inferences drawn based on relevant quantities outcomes and their probabilities. The DEA procedure is explained in the following section.

#### 3.3.1 Data Envelopment Analysis (DEA)

The DEA approach, also called the CCR DEA model after the names of the original proponents (Charnes, Cooper and Rhodes), is an analytical technique used for performance evaluation and benchmarking (Charnes et al., 1978). According to Talluri (2000), it is a multi-factor productivity exploration model used for assessing relative efficiencies of a homogenous set of decision making units (DMUs). OECD (2001) affirmed that the distinction and identification of “technical” and “efficiency” change is at the heart of DEA. For this study, the DMUs are cassava farm enterprises operating in the presence of multiple input and multiple output production factors.

Following Talluri (2000), the authors defined technical efficiency score for each farm unit as a ratio of weighted sum of outputs to the weighted sum of inputs (equation 1).

$$Efficiency = \frac{\text{weighted sum of outputs}}{\text{weighted sum of inputs}} \quad (1)$$

The weights are calculated by means of mathematical programming under an assumption of constant returns to scale.

The model proposed by Charnes et al. (1978) uses a “ratio-form” that defines “relative efficiency” as “ratio of outputs to inputs” (Cooper et al., 2004, page 8). They authors confirmed that efficiency is viewed relation to the “empirically available information” and suggested that each “DMU is to be rated as fully (100%) efficient on the basis of available evidence if and only if the performances of other DMUs does (sic) not show that some of its inputs or outputs can be improved without worsening some of its other inputs or outputs” Cooper et al. (2004, page 1). Accordingly, “the measure of efficiency of any DMU is obtained as the maximum of a ratio of weighted outputs to weighted inputs subject to the condition that the similar ratios for every DMU be less than or equal to unity” (Charnes et al., 1978, page 430).

Suppose there are  $n$  DMUs, each of which uses  $m$  inputs to produce  $s$  outputs, then the relative efficiency score of a test DMU,  $p$ , is obtained by solving the following model proposed by Charnes et al. (1978) and applied by Cooper et al. (2004).

$$\begin{aligned} \maximize \quad & \frac{\sum_{k=1}^s v_k y_{kp}}{\sum_{j=1}^m u_j x_{jp}} \\ \text{subject to} \quad & \frac{\sum_{k=1}^s v_k y_{ki}}{\sum_{j=1}^m u_j x_{ji}} \leq 1 \quad \forall_i \\ & v_k, u_j \geq 0 \quad \forall k, j \end{aligned} \tag{2}$$

where,  $k = 1 \dots s$ ,  $j = 1 \dots m$ ,  $i = 1 \dots n$ ;  $y_{ki}$  = amount of output  $k$  produced by DMU $i$ ;  $x_{ji}$  = amount of input  $j$  utilized by DMU $i$ ;  $v_k$  = weight given to output  $k$ ; and  $u_j$  = weight given to input  $j$ .

The equation (2) is a quotient function. It is a fractional programme but, can be converted into a linear programme (Charnes et al. 1978) represented in equation (3).

$$\begin{aligned} \maximize \quad & \sum_{k=1}^s v_k y_{kp} \\ \text{subject to} \quad & \sum_{j=1}^m u_j x_{jp} = 1 \\ & \sum_{k=1}^s v_k y_{ki} - \sum_{j=1}^m u_j x_{ji} \leq 0 \quad \forall_i \\ & v_k, u_j \geq 0 \quad \forall k, j \end{aligned} \tag{3}$$

The linear problem in equation (3) is run  $n$  times for each of the respective farm enterprises ( $n=96$ ) to identify the relative efficiency scores of each farm firm (DMU). Consequently, the input and output weights that maximize the efficiency score is selected for each farm unit.

For every inefficient DMU, CCR DEA identifies a set of corresponding “efficient” units that can be utilized as benchmarks for improvement. The benchmarks are obtained from the following dual problem (equation 4).

$$\begin{aligned} \minimize \quad & \theta \\ \text{subject to} \quad & \sum_{i=1}^n \lambda_i x_{ji} - \theta x_{jp} \leq 0 \quad \forall_j \\ & \sum_{i=1}^n \lambda_i y_{ki} - y_{kp} \geq 0 \quad \forall_k \\ & \lambda_i \geq 0 \quad \forall_i \end{aligned} \tag{4}$$

where  $\theta$  = efficiency score, and  $\lambda_s$  = dual variables.

According to Talluri (2000), the rule of decision making is that a DMU is assumed efficient if its efficient score is unity, otherwise it is considered inefficient. The following definitions apply:

- “The performance of  $DMU_o$  is fully (100%) efficient if and only if both (i)  $\theta^* = 1$  and (ii) all slacks  $s_i^{-*} = s_r^{+*} = 0$ ,” (Cooper et al. (2014, page 11).
- “The performance of  $DMU_o$  is weakly efficient if and only if both (i)  $\theta^* = 1$  and (ii)  $s_i^{-*} \neq 0$

and/or  $S_r^{+*} \neq 0$  for some  $i$  and  $r$  in some alternate optima” (Cooper et al. (2014, page 11).

The “ $S_i^{-*}$ ” and “ $S_r^{+*}$ ” represent the “input slack” and the “output slack” and “o” is a focal DMU respectively. Deriving the “slacks” in the context of the CCR DEA model requires solving the second stage of the “linear programming model” designed for the slacks as follows:

$$\begin{aligned} & \text{Maximize } \sum_{i=1}^m s_i^- + \sum_{r=1}^s s_r^+ \\ & \sum_{j=1}^n \lambda_j x_{ij} + s_i^- = \theta^* x_{i0} \\ & \qquad \qquad \qquad ; \text{ for } i = 1, \dots, m \\ & \qquad \qquad \qquad (5) \end{aligned}$$

$$\begin{aligned} & \sum_{j=1}^n \lambda_j y_{rj} - s_r^+ = y_{r0} \\ & \qquad \qquad \qquad ; \text{ for } r = 1, \dots, s \\ & \lambda_j \geq 0 \\ & \qquad \qquad \qquad ; \text{ for } j=1, \dots, n \end{aligned}$$

Consequently, an input-oriented CCR DEA model that includes the “slacks” is given as:

$$\begin{aligned} & \text{Minimize } \theta - \varepsilon \left( \sum_{i=1}^m s_i^- + \sum_{r=1}^s s_r^+ \right) \\ & \sum_{j=1}^n \lambda_j x_{ij} + s_i^- = \theta x_{i0} \\ & \qquad \qquad \qquad ; \text{ for } i = 1, \dots, m \\ & \qquad \qquad \qquad (6) \end{aligned}$$

$$\begin{aligned} & \sum_{j=1}^n \lambda_j y_{rj} - s_r^+ = y_{r0} \\ & \qquad \qquad \qquad ; \text{ for } r = 1, \dots, s \\ & \lambda_j \geq 0 \\ & \qquad \qquad \qquad ; \text{ for } j=1, \dots, n \end{aligned}$$

Similarly, an “output-oriented” CCR DEA model with the slacks is given as:

$$\begin{aligned} & \text{Maximize } \phi - \varepsilon \left( \sum_{i=1}^m s_i^- + \sum_{r=1}^s s_r^+ \right) \\ & \sum_{j=1}^n \lambda_j x_{ij} + s_i^- = x_{i0} \\ & \qquad \qquad \qquad ; \text{ for } i = 1, \dots, m \\ & \qquad \qquad \qquad (7) \end{aligned}$$

$$\begin{aligned} & \sum_{j=1}^n \lambda_j y_{rj} - s_r^+ = \phi y_{r0} \\ & \qquad \qquad \qquad ; \text{ for } r = 1, \dots, s \\ & \lambda_j \geq 0 \\ & \qquad \qquad \qquad ; \text{ for } j=1, \dots, n \end{aligned}$$

In the objective function of equations (6) and (7), “ $\theta$ ” and “ $\phi$ ” represent the input-based and output-based efficiency scores respectively, and “ $\varepsilon$ ” is a “non-Archimedean” quantity that is known to infinitesimally small – reasonably smaller than any “real positive number”. It permits for the “minimization” of “ $\theta$ ” or “ $\phi$ ” to anticipate the “optimization” of the slacks,  $S_i^+$  and  $S_i^-$  (Ozcan, 2014, page 45).

It was noted by Talluri (2000, page 9) that CCR DEA model “is primarily a diagnostic tool and does not prescribe any reengineering strategies to make inefficient units efficient.” If improvements are needed it behooves on the managers to study and understand what has led to efficiency on the side of efficient DMUs, and apply the emerging strategies for transformation of the inefficient units. A number of advantages are linked with the use of DEA. Among its strengths is its ability to analyse cases involving numerous number of inputs and outputs, ability to work with inputs and outputs denominated in varied units, juxtaposing the DMUs and making judgment of each in relation to others or set of others, and not demanding a hypothesis of any functional form for inputs and outputs. The associated shortcomings are that being an “extreme point” model any simple bang may create unanticipated undesirable difficulties, its design that produces a distinct “linear programme” for every

DMU makes calculations involving large numbers of DMUs extremely burdensome, it can predict comparative efficiency of each DMU but does not congregate to complete efficiency, and that as a “nonparametric” method its use makes problematic the statistical test of hypothesis.

For this study, the input and output variables included for the empirical DEA include the average yield of cassava linked to each farm unit measured in tonnes per hectare (FYLD<sub>*i*</sub>); farm area cultivated by each farm unit measured in hectares (RFMS<sub>*i*</sub>); cost of labor (LBCS); quantity of stalk cuttings used by each farm unit measured in bundles per hectare (QSTM<sub>*i*</sub>);<sup>2</sup> quantity of fertilizer used by each farm unit measured in kilogram per hectare (FERT<sub>*i*</sub>); quantity of herbicide applied by each farm unit stated in liters per hectare (HERB<sub>*i*</sub>).

### 3.3.2. Regression analysis

The ordinary least square (OLS) estimation of the relationship between the endogenous variable and two or more exogenous variables usually produces estimators of the standard error and a coefficient of multiple determination. Suppose a variable ( $y_i$ ) assumes some values determined by values assumed by other set of variables ( $x_i$ ). In implicit form, the statement that  $y_i$  is associated with the  $x_i$ s is given as

$$y_i = f(x_1, x_2, \dots, x_k) \quad (8)$$

where  $y_i$  is the reliant variable, and  $x_i$  (for  $i=1, \dots, k$ ) is a set of  $k$  independent variables.

The coefficient of multiple determination measures the relative amount of variation in the endogenous variable ( $y_i$ ) explained by the regression relationship it has with the explanatory variables ( $x_i$ ). The F-statistics tests the significance of the coefficients of the  $x_i$  as a group. It is the statistics associated with the null hypothesis of no evidence of significant statistical regression relationship between  $y_i$  and the  $x_i$ , against the alternative hypothesis of evidence of significant statistical relationship. The critical F-value has  $n$  and  $n-k-1$  degrees of freedom,  $n$  being the number of respondents and  $k$ , the number of independent variables. The “standard error” is the measure of inaccuracy about the regression coefficients. The z-statistics is used in testing the null hypothesis that the parameter estimates are statistically equal to zero against the alternative hypothesis that the parameter estimates are statistically different from zero. If the computed z-value exceeds the critical value, we reject the null hypothesis and conclude that the parameter estimates differ significantly from zero.

In this study, the empirical model for the estimation of the determinants of efficiency of the cassava farm units was specified as follow:

$$Eff_i = \beta_0 + \beta_1 LPRP_i + \beta_2 LBCS_i + \beta_3 AGCH_i + \beta_4 FYLD_i + \beta_5 RAGE_i + \beta_6 REXP_i + \beta_7 REDU_i + \beta_8 RFMS_i + \beta_9 FERT_i + \beta_{10} QSTM_i + \beta_{11} RHHS + \zeta_i \quad (9)$$

where  $Eff_i$  is the efficiency score for farmer  $i$ ;  $\beta_i$  (for  $i = 0, 1, \dots, 10$ ) are parameters to be estimated, and  $\zeta_i$  is the stochastic error term. The definition and detailed explanation of the included variables in the efficiency model follow in the next section.

### 3.3.3. Variables used in the efficiency regression model

The dependent variable,  $Eff_i$ , is defined as the DEA efficiency score for respondent farmer  $i$ . It is hypothesized that  $Eff_i$  is influenced by the following exogenous variables.

Land preparation cost (LPRP<sub>*i*</sub>) or the total value of the local currency (naira) spent on the major land preparation activities of ploughing, harrowing and ridging financed by the farmer. Efficiency is expressed as the weighted sum of output divided by the weighted sum of inputs (Talluri, 2000). Taking the monetary value of the output and the inputs, it means that any transaction that would lead to an increase in the denominator (input cost) would lead to reduction in efficiency. Increase in the amount expended in land preparation would therefore lead to increase in the total input cost and reduction in efficiency. Therefore it is expected that the cost of land preparation will negatively affect efficiency ( $\beta_1 < 0$ ).

Labour cost (LBCS<sub>*i*</sub>) or total amount of the local currency expended by the farming unit to procure the labour services for the farm firm. Like land preparation cost of labour would also add to the total cost of inputs and have a negative effect on efficiency ( $\beta_2 < 0$ ).

Cost of herbicides (AGCH<sub>*i*</sub>) is the total amount of the local currency spent by the farm unit in the procurement and application of herbicides. Like costs of land preparation and labour, cost of herbicides would also add to the total production cost and reduced efficiency. It is predicted that like other cost items, the cost of agrochemicals will have a negative influence on efficiency ( $\beta_3 < 0$ ).

The yield of the cassava yield of the farming unit (FYLD<sub>*i*</sub>) during the period of study. Unlike the cost elements higher yield would result to increased output and higher revenue given that price of roots remained unchanged. Therefore, it is expected that yield will be positively related to efficiency ( $\beta_4 > 0$ ).

The head of the farming unit’s farming experience (REXP<sub>*i*</sub>) is the defined as total number of years he or her had spent as an independent decision-taker in cassava farming. The effect of farming experience on efficiency could be mixed (Iduma et al., 2016). The effect could be negative if the elderly and more experienced heads of

farming units who are somewhat “traditional”, and as such less willing to give up their old practices to embrace modern practices that would result to production efficiency. On the contrary, the effect could be positive if the older farmers are less conservative and more willing to apply improved farming practices for improved productivity and efficiency. It could also be that the older and experienced farmers by virtue of the length of time they have put into cassava farming have better knowledge of the farming operations and the best time to perform them to achieve efficiency. It is predicted that REXP will have a positive influence on efficiency ( $\beta_6 > 0$  or  $\beta_6 < 0$ ).

Age of the head of the farming unit ( $RAGE_i$ ) is defined in years. Like years of experience, the influence of age on farming efficiency could be either negative or positive ( $\beta_5 > 0$  or  $\beta_5 < 0$ ).

The farmer’s level of education of the head of the farming unit ( $REDU_i$ ) is captured as: 0 if he/she had no formal education, 1 if she/he had only primary education, 2 if she/he had maximum of junior secondary education, 3 if she/he attained not more than senior secondary education, 4 if she/he attempted, but did not complete post-secondary education, and 5 if she/he completed the tertiary education completed. The positive effect of education on the production efficiency of farm decision making units had been established by Coelli and Battese (1996), even as Bamire et al. (2002) also confirmed the positive influence of proper schooling on adoption of improved farming practices. Therefore, it is postulated that REDU will have a positive effect on efficiency ( $\beta_7 > 0$ ).

The farm size ( $RFMS_i$ ) is the total land area devoted to cassava production by farming unit during the period studied expressed in hectares. It has been observed that the minor farms often achieve greater “income per hectare” and are more technically efficient than the bigger farms (Masterson 2007). This could result from the direct supervisory and daily oversight roles of the owner. But on the other hand, the owner of a large farm often has more capital and could take advantage of the economy of large-scale production to achieve higher return and efficiency. Therefore, the influence of farm size on efficiency is predicted to be either positive or negative ( $\beta_8 > 0$  or  $\beta_8 < 0$ );

The farming unit’s fertilizer use status ( $FERT_i$ ) is captured as a dummy variable: 1 if fertilizer was applied, 0 if fertilizer was not applied. Fertilizer use is expected to have a positive influence on efficiency if the recommended quantities are applied under the demanding soil condition (Njeru, 2010). When the use is contrary to the recommended practice or does not consider the soil fertility condition, it could lead to inefficiency in cassava production. Thus, it is expected that the influence of FERT on efficiency will be either positive or negative ( $\beta_9 > 0$  or  $\beta_9 < 0$ ).

The quantity of improved stalks bundles used by the farming unit ( $QSTM_i$ ) during the farming period. It is defined in number of stalk bundles per hectare. It is predicted that QSTM will have either a positive or negative effect on relation to efficiency ( $\beta_{10} > 0$  or  $\beta_{10} < 0$ ). Increasing would result to increase in efficiency if by such increase the spacing was reduced between the rows of cassava stands (Adeyemo et. al. 2010). It would lead to decrease in efficiency if increasing the quantity of stems resulted to unnecessary waste of the planting materials by failing to cut the stakes according to the standard best practice.

The household size ( $RHHS_i$ ) refers to the number of persons that are resident in the head of farm unit’s house and share meals together. It is predicted that the influence of RHHS on the efficiency of cassava farming will be mixed ( $\beta_{11} > 0$  or  $\beta_{11} < 0$ ). The effect will be negative when the large household size leads to increased household expenditure in an effort to sustain a prevailing living standard, thereby draining the available capital that otherwise would have been deployed to the farm to enhance efficiency. The effect will be positive if the household by virtue of its large size would supply part of the labour needs of the farm to reduce reliance on hired labour. If this happens the funds, it becomes possible to invest the unspent funds in other areas of the farm business to enhance efficiency.

### 3.3.4. Estimation procedure

The LIMDEP Version 9.0 was used to estimate the input-oriented DEA efficiency scores while the estimation of the OLS regression parameters of the efficiency model of equation (6), tests of redundancy and calculation of other statistics were performed using the Standard EViews 7 windows. Only the heteroskedasticity-consistent linear form of the OLS estimations were derived and reported. Heteroskedasticity is the unequal variance in the regression errors often associated with cross-section data (Hayes and Cai, 2007; Hayes et al., 1999). In the presence of heteroskedasticity, the OLS estimates remain consistent but the conventional computed standard errors would no longer be valid. Redundancy test was conducted on the explanatory variables to ascertain the variable or set of variables that were making significant contribution to the efficiency model. Consequently, only the variables that were not found to be redundant were retained in final model.

### 3.3.5. Redundancy test of variables

The initial estimation was followed by the redundant tests of included variables using the test procedure provided by EViews as previously applied elsewhere (Ojiako et al., 2014). The redundant test was aimed at assessing the statistical significance of each or a collection of the included variables with a view to confirming if it or they could be dropped out of the model without having significant influence in the result. The test is as follows:

$$H_0 : \beta_i = 0 \text{ (beta coefficient equals zero and variable is insignificant)}$$

$$H_1 : \beta_i \neq 0 \text{ (beta coefficient (s) is different from zero and variable is significant)}$$

The F-values and the log-likelihood ratios are the test statistics. The F-value has a precise limited sample F-distribution in the null hypothesis if the errors are independent and identically spread normal chance factors. The degree of freedom for the numerator is the number of coefficient restraints under  $H_0$  while for the denominator it is equivalent to the total regression degrees of freedom. The likelihood ratio test is an “asymptotic” test, distributed as  $\chi^2$  whose degrees of freedom are equivalent to the number of debarred variables under  $H_0$ . For decision-taking, the rule is to reject  $H_0$  if the F-value is statistically significant ( $p < 0.05$ ). This will lead to the conclusion that the beta coefficient associated with the specific factor differs from zero, signifying that the factor is a significant contributor to the efficiency model.

#### 4. Results and discussion

##### 4.1. Descriptive statistics of included variables

The descriptive statistics of all variables is presented in Table 1.

Table 1. Descriptive statistics of variables

Variable	Short form	Measure	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera
Cost of land preparation	LPRP	(₦)	45,494.2	38000.0	119000.0	8200.0	26050.9	0.8	2.7	11.1
Labor cost	LBCS	(₦)	173299.6	146125.0	503400.0	38500.0	84180.8	1.5	5.9	69.1
Cost of agrochemicals	AGCH	(₦)	14437.7	11000.0	80000.0	2000.0	11794.1	2.7	12.9	506.5
Yield	FYLD	t/ha	12.4	10.0	30.0	4.0	6.5	1.8	4.6	58.2
Age of farmers' head	RAGE	years	48.3	48.0	75.0	22.0	9.4	0.2	3.2	0.7
Farming experience	REXP	years	16.0	14.5	55.0	3.0	10.6	1.1	4.3	27.0
Education	REDU	discrete	2.9	3.0	6.0	1.0	0.9	0.3	3.8	3.6
Farm size	RFMS	hectares	3.2	2.0	20.0	0.2	2.9	2.7	13.3	531.6
Fertilizer use status	FERT	dummy	0.5	1.0	1.0	0.0	0.5	-0.2	1.0	15.7
Fertilizer application	FTLZ	kilogram	118.1	150.0	600.0	0.0	129.3	0.9	4.0	19.6
Quantity of stems	QSTM	bundles	56.4	60.0	80.0	4.0	12.7	-2.8	11.3	392.0
Household size	RHHS	Number	7.5	7.0	15.0	2.0	3.1	0.5	2.7	4.8

1 bag (50 kg, NPK 15-15-15 fertilizer); Naira/dollar exchange rate at the time of study was ₦151/US1.

Source: Calculated using Field Survey Data

The average cost incurred by the farming units on land preparation was ₦45,494.15 (about US\$301). It ranged from ₦8,200 or US\$54.30 to ₦119,800 or US\$788.08 giving a standard deviation of 26,050. The average costs were also calculated as ₦173,299.60 (or US\$1,147.68) for labour and ₦14,437.66 (or US\$95.61) for agrochemicals that included herbicides and pesticides for pre-planting stem treatment. It shows that labour cost accounted for a largest share of the production cost of cassava. This corroborates the study by Nandi et al. (2011) that also found that labor accounted for about 65.2% of the total production cost of cassava in Obubra area of Cross River State, Nigeria. Also, Ettah and Angba (2016) held that labour with 48.45% was the highest contributor to the total variable cost of cassava production in Cross River State, Nigeria. The descriptive values are also calculated for as 12.35 tons/ha for yield, 48.33 years for farming units head's age, 16 years for cassava farming experience, 3.17 ha for farm size and about 7 persons for household size. Other averages reported are 2.87 for education (meaning that an average farmer completed the junior secondary school education), 0.54 for fertilizer use (or that 54% used fertilizer). The actual average quantity of fertilizer used was calculated as 118.09 kg/ha, and the average quantity of stems as 56.38 bundles/ha. The maximum and minimum values of all variables with the associated standard deviation, coefficients of skewness and Kurtosis are also presented on the Table 1.

##### 4.2. DEA output of technical efficiency of cassava farming units

Data Envelopment Analysis was used to estimate the technical efficiency of the 96 cassava farming units, which are the DMUs for this study, using the input-oriented approach with constant return to scale. The summary of the output is presented in Table 2 (calculated efficiency scores for all DMUs is presented in Appendix I).

Table 2. Summary of Efficiency scores of the cassava decision making units (DMUs)

Description	Frequency	Percentage frequency	Mean	Std. dev.	Minimum	Maximum
Eff<0.4	18	18.75	0.295	0.058	0.213	0.386
0.4<Eff<0.6	32	33.33	0.506	0.057	0.409	0.594
0.6<Eff<0.8	17	17.71	0.690	0.057	0.600	0.780
Eff>0.8	29	30.21	0.985	0.044	0.837	1.000
All (Total)	96	100.00	0.644	0.261	0.213	1.000

Source: Calculated using Field Survey Data

Over 30.2% of the cassava farming units were found to be have technical efficient scores greater than 0.8.

This includes 26.04% with efficiency score of 1.0 and 3.06% with scores that from 0.81- 0.99. Farming units with efficiency scores from 0.6-0.8 constitute 17.7% of the sample while those with scores from 0.4-0.6 consist of 33.3%. This fully technically efficient farming units were those producing on the frontier, in comparison to others. They are the DMUs using the right mix of inputs and to achieve maximum output. Perhaps, the bias introduced in the calculation by the relatively small sample size might partly be responsible for having over one-quarter of the DMUs returning the perfect efficiency score. As explained by Machek and Špička (2014), a possible inconveniences of an econometric/ mathematical programming techniques like the DEA is that when the data sample is small the frontier estimation may be biased leading to an unacceptably large share of the sample appearing to be fully efficient (Machek and Špička, 2014).

In the neighbourhood of 73.9% of the DMUs were inefficient in resource use with efficiency scores defined within the range  $0 \leq EFF < 1$ . Similar inefficiencies were reported in Imo State in the south-east zone of Nigeria, where a similar study that applied the DEA approach also established that majority of the cassava farming units in the area “operated very far away from the efficiency frontier” (Ohajianya et al., 2014, page 458). The inefficient DMUs must be reduced or adjust their inputs mix to the acceptable proportions to achieve the desired levels of efficiency. For example, consider the case of DMU001 with efficiency score of 0.27366, which is 0.72634 less than the perfect score of 1. It implies that the farming unit must improve its efficiency, or reduce its inefficiencies by adjusting its mix of certain inputs (the analysis is using an input-oriented approach) up to the tune of 72.63%. In the same way, DMU051 with efficiency score calculated as 0.46930 must have to improve its efficiency or reduce its inefficiencies by adjusting the mix of certain inputs by 53.07%. Similar adjustments are also required for other inefficient DMUs (Appendix I).

It has been pointed out that the required input adjustments (for example, 72.63% for DMU001 or 53.07% for DMU051) are called “total inefficiencies” (Ozcan, 2014). They represent both the “amount of proportional reductions” and the amount of ‘slack’ for the affected DMUs that could not reach attain the efficiency targets at the frontier even after the necessary adjustments have been carried out (Ozcan, 2014). The answer to the “question” relating to the inputs to adjust, the required magnitudes and the proportion accounted for by “slacks” require running the second stage of CCR DEA model, which is not covered within the scope of this investigation.

### 4.3. Efficiency determinants

The heteroskedasticity-consistent estimates (HSCE) of the OLS regression model were derived for each of the explanatory variables. Evidence from literature suggests that HSCE can be quite useful in alleviating the worries that a researcher might have about the effects of heteroskedasticity on inferential tests in OLS regression (Hayes and Cai, 2007). The output of the regression analysis that included all variables is presented in Appendix II. Based on the resultant estimates, the White redundant variable test was conducted on each variable. The test result is reported in Table 3.

Table 3: Output of redundant test for excluded variables

Variable (s)	Null Hypothesis (Ho)	F-statistic	Probability	Log. Likelihood ratio	Probability	Decision on $H_0$	Conclusion
LPRP	$\beta_1=0$	1.428690	0.235424	1.623663	0.202582	Accept	LPRP redundant
LBCS	$\beta_2=0$	0.521793	0.472133	0.596258	0.440009	Accept	LBCS redundant
AGCH	$\beta_3=0$	0.797275	0.374522	0.909535	0.340238	Accept	AGCH redundant
FYLD	$\beta_4=0$	2.055093	0.155500	2.326801	0.127163	Accept	AYLD redundant
RAGE	$\beta_5=0$	1.168801	0.282817	1.330386	0.248737	Accept	RAGE redundant
REXP	$\beta_6=0$	6.623171**	0.011866	7.301365***	0.006890	Reject	REXP not redundant
REDU	$\beta_7=0$	0.270955	0.604095	0.310095	0.577622	Accept	REDU redundant
RFMS	$\beta_8=0$	1.020915	0.315274	1.163092	0.280825	Accept	XFMS redundant
FERT	$\beta_9=0$	8.450100***	0.004693	9.219432***	0.002395	Reject	FERT not redundant
QSTM	$\beta_{10}=0$	8.162748***	0.005417	8.920327***	0.002820	Reject	QSTM not redundant
RHHS	$\beta_{11}=0$	0.052146	0.819939	0.059758	0.806879	Accept	RHHS redundant
LPRP, LBCS, AGCH, RAGE, RFMS, RHHS	$\beta_1=\beta_2=\beta_3=\beta_4=\beta_5=\beta_6=\beta_7=\beta_8=\beta_{11}=0$	0.898536	0.521782	7.898864	0.443411	Accept	All variables redundant

\*\*\*=significant at 1% level; \*\*=significant at 5% level; \*=significant at 10% level; NA=not applicable

Source: Calculated using Field Survey Data

The redundant test results revealed only three of the explanatory variable as making significant contribution to the originally estimated efficiency model. The significant variables are farming experience (REXP), fertilizer use (FERT), and quantity of stems used (QSTM). The test-statistics calculated reported as  $F=6.62$  ( $p<0.05$ ) for

farming experience,  $F=8.45$  ( $p<0.01$ ) for fertilizer use and  $F=8.16$  ( $p<0.01$ ) for improved stalk cuttings, as well as the Log-Likelihood ratios, were high enough to cause the rejection of  $H_0 : \beta_i = 0$

The authors concluded that the beta coefficients were non-negative and the 3 variables were not redundant. Contrarily, all the other variables were found to be redundant and were adding less value to the model. The last row of Table 3 is the result of redundancy test that considered the set of all “redundant variables” together. It also led to a similar conclusion. The implication is that the set of variables were individually and collectively redundant. Moving forward, the redundant variables were dropped out of the empirical model. Consequently, the model was run again with only the retained variables. The regression output is presented in Table 4.

Table 4. Factors influencing the efficiency of cassava farming units

Variable	Code	Expected sign	Coefficient	Std. Error	t-statistic	Probability
Constant	CON	N/A	0.9349***	0.1026	9.1143	0.0000
Cassava farming experience	REXP	positive	0.0076***	0.0023	3.2526	0.0016
Use of fertilizer	FERT	negative	-0.1818***	0.0493	-3.6908	0.0004
Quantity of stems	QSTM	negative	-0.0056***	0.0016	-3.3902	0.0010
R-squared			0.2019		Mean dependent variable	0.6438
Adjusted R-squared			0.1753		S.D. dependent variable	0.2635
S.E. of regression			0.2393		Akaike info criterion	0.0195
Sum squared residuals			5.1542		Schwarz criterion	0.1277
Log likelihood			3.0836		F-statistic	7.5914
Durbin-Watson stat			1.8928		Prob(F-statistic)	0.0001

\*\*\*=significant at 1% level; \*\*=significant at 5% level; \*=significant at 10% level; NA=not applicable

Source: Calculated using Field Survey Data

Cassava farming experience has a positive effect on efficiency meaning that the higher the number of years of experience the more efficient the farmer. Nandi et al (2011) investigated the economics of cassava production in Obubra area of Cross River State in Nigeria and also found that farming experience was among the significant factors that had positive influence on cassava production. Unlike this present study, the Obubra study used cassava production volume as a dependent variable. Elsewhere, Ogisi et al. (2013) also found that farming experience had a significant positive effect on cassava production and productivity in Ika area of Delta State, Nigeria. However, the aforementioned positive influence of farming experience on cassava production fails to agree with the result of the work conducted by Adeyemo et al. (2010) in the western area of Nigeria, which found that farming experience was a major contributor to inefficiency in cassava production. The implication of the finding from this study is that the older and more experienced farmers combined their versatile knowledge of the farming operations they accrued over the years with willingness to adopt and use improved farming practices to achieve efficiency.

Fertilizer application status is significant at  $p<0.01$  level, but negatively related to efficiency of cassava production. It suggests that as the head of farming units were becoming more willing to use fertilizer their efficiency level dropped. This is an unfortunate scenario, which might have resulted from possible wastage and use of fertilizer when its value addition to the soil fertility is minimal. Wastage often arose out of farming units' failure to follow the recommended best practices, which includes the cost-effective dosage/quantity, application time and method. Also, a prior knowledge of the soil fertility condition is required and can only be determined through conducting soil testing prelude to land preparation. In a situation where the head of a farming unit has no knowledge of the soil fertility status because soil testing was not conducted, even the application of the recommended fertilizer dosage on a highly or moderately fertile soil may as well result to wastage because it will add little or no value to the soil fertility level. Obliviousness, poverty, and lack of affordable training opportunities are among the causes of farmers' indifference to abide by the soil testing requirement as a standard best practice in cassava production. This partly corroborates the argument that technical efficiency differences could be explained in the context of relative access to “training, knowledge and experience, incentive/motivation” (Ahmed et al., 2005). Elsewhere, Osun et al (2014) also established a negative influence of fertilizer application status on production efficiency while Adeyemo et al. (2010) found that cost of fertilizer had a positive effect on production and productivity of cassava in Ogun State of the south-west zone of Nigeria.

The third variable, quantity of stems, produced a negative sign, meaning that as the quantity of stem cuttings (planting materials) increased the levels of efficiency dropped. This can also be explained around the need to avoid wastage of planting materials by ensuring that only the appropriate quantity is bought and used at any point in time. The recommended optimal quantity is 50 bundles/ha (with each bundle containing 50 stems each measuring 1 meter in length). This will give a plant population of 12,500 stands/ha using the recommended plant spacing of 1 m x 0.8 m. It is a common practice among farming units to deviate from this recommended practice: (a) if a farmer is in the habit of cutting stems at 25 cm length, a bundle will produce 200 rather than 250 cuttings and 50 bundles will generate a plant population of 10,000 stands/ha, and to increase the plant population

to 12,500 stands would require increasing the number of bundles by 25% to 62.5 bundles; (b) if a farmer is in the habit of cutting stems at 30 cm length, 50 bundles can only generate 8,333 stem cuttings and equivalent plants stands, and to increase the plant population to 12,500 stands would require increasing the number of bundles by 50% to 75 bundles; (c) if a farmer is in the habit using 1 m x 1 m plant spacing, then 1 hectare farmland can only accommodate a plant population of 10,000 stands, which is 20% less than the 12,500 stands/ha recommended plant population. Each of these and other associated cases are potential sources of inefficiency in use of planting materials that are associated with farming units' practices. Other studies had also revealed the significance of stalk cuttings in cassava production and productivity (Eze and Nwibo, 2014; Nandi et al., 2011; Ogisi et al., 2013).

In summary, it is found that each of the three retained variables was significant at 1% level with associated t-statistics of 3.25 for farming experience, -3.69 for fertilizer use, and -3.39 for improved stems. All the variables produced the a priori signs. Incidentally, their joint contributing power to the efficiency model, as determined by the  $R^2$  was low at only 20%, although the overall model was statistically significant (F-value = 7.5914;  $p < 0.01$ ). It suggests that apart from the three variables there are others that determine efficiency, which incidentally were omitted in the model.

## 5. Conclusion

An investigation was conducted into the cassava production efficiency and its determinants among farming and decision making units. Ninety-six heads of farming units selected from eight states of Nigeria at their early years of participation in the implementation of the IITA-Nestlé Nigeria cassava starch value chain project, 2011-2015 were studied. Results confirm that majority of the farming units were inefficient in resources allocation decisions. Most of the factors considered for inclusion in the efficiency determinant model could not be retained, having been found to be individually and collectively redundant. Only three variables were identified for their influence on efficiency: farming experience, fertilizer use and stems cuttings. The elderly and better experienced farmers combined their versatile knowledge of farming operations garnered over the years with willingness to adopt and use improved farming practices to achieve efficiency. Contrary to expectation, fertilizer and stems uses were associated with less efficiency, an unfortunate situation that could result from misapplication or wastage of the vital resources. The findings highlight the need for adequate training and capacity enhancement of the farmers and heads of farming units to improve their levels of efficiency. The emerging evidence provided the baseline information for the development of the training modules used in the course of implementation of the cassava starch project.

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### Appendix I. Efficiency Scores of the DMUs

DMU Code	Efficiency scores ( $\theta$ )	Reciprocal (1/ $\theta$ )	DMU Code	Efficiency scores ( $\theta$ )	Reciprocal (1/ $\theta$ )	DMU Code	Efficiency scores	Reciprocal (1/ $\theta$ )
DMU001	0.27366	3.6542	DMU033	0.27338	3.6579	DMU065	1.00000	1.0000
DMU002	0.23638	4.2304	DMU034	0.48798	2.0493	DMU066	0.52177	1.9166
DMU003	1.00000	1.0000	DMU035	0.38397	2.6044	DMU067	1.00000	1.0000
DMU004	0.21279	4.6995	DMU036	0.51609	1.9376	DMU068	1.00000	1.0000
DMU005	0.83678	1.1951	DMU037	0.51033	1.9595	DMU069	0.74276	1.3463
DMU006	0.57115	1.7508	DMU038	1.00000	1.0000	DMU070	0.70216	1.4242
DMU007	0.40977	2.4404	DMU039	1.00000	1.0000	DMU071	0.76841	1.3014
DMU008	0.56529	1.7690	DMU040	1.00000	1.0000	DMU072	0.56435	1.7720
DMU009	0.25017	3.9972	DMU041	0.54277	1.8424	DMU073	0.35795	2.7937
DMU010	1.00000	1.0000	DMU042	0.55800	1.7921	DMU074	0.48663	2.0549
DMU011	0.42857	2.3333	DMU043	0.50129	1.9948	DMU075	0.46498	2.1506
DMU012	0.38333	2.6087	DMU044	1.00000	1.0000	DMU076	0.58886	1.6982
DMU013	0.56320	1.7756	DMU045	0.60509	1.6526	DMU077	0.42265	2.3660
DMU014	0.22727	4.4000	DMU046	0.28843	3.4670	DMU078	1.00000	1.0000
DMU015	0.52051	1.9212	DMU047	0.43407	2.3038	DMU079	0.26708	3.7442
DMU016	0.53497	1.8693	DMU048	0.64748	1.5444	DMU080	0.49784	2.0087
DMU017	0.63105	1.5847	DMU049	0.63931	1.5642	DMU081	0.35436	2.8220
DMU018	1.00000	1.0000	DMU050	0.56569	1.7678	DMU082	1.00000	1.0000
DMU019	0.33495	2.9856	DMU051	0.46930	2.1309	DMU083	0.78000	1.2821
DMU020	0.43563	2.2955	DMU052	1.00000	1.0000	DMU084	0.47868	2.0891
DMU021	1.00000	1.0000	DMU053	0.72661	1.3763	DMU085	0.24447	4.0905
DMU022	1.00000	1.0000	DMU054	0.84198	1.1877	DMU086	0.60000	1.6667
DMU023	1.00000	1.0000	DMU055	1.00000	1.0000	DMU087	1.00000	1.0000
DMU024	0.31078	3.2177	DMU056	0.91752	1.0899	DMU088	1.00000	1.0000
DMU025	0.25208	3.9669	DMU057	1.00000	1.0000	DMU089	0.76198	1.3124
DMU026	0.41884	2.3876	DMU058	0.44948	2.2248	DMU090	1.00000	1.0000
DMU027	0.38636	2.5883	DMU059	0.57079	1.7519	DMU091	1.00000	1.0000
DMU028	0.66000	1.5152	DMU060	0.69310	1.4428	DMU092	0.95752	1.0444
DMU029	0.72000	1.3889	DMU061	0.59362	1.6846	DMU093	0.44648	2.2398
DMU030	0.49438	2.0227	DMU062	0.64392	1.5530	DMU094	0.58979	1.6955
DMU031	0.26667	3.7500	DMU063	0.73306	1.3641	DMU095	1.00000	1.0000
DMU032	1.00000	1.0000	DMU064	1.00000	1.0000	DMU096	0.67534	1.4807

Source: Calculated using Field Survey Data

### Appendix II: Output of heteroskedasticity-consistent estimates of the OLS model involving all variables

Variable	Code	Expected sign	Coefficient	Std. Error	t-Statistic	Probability
Constant	CONS	n/a	1.229959	0.200500	6.134467	0.0000
Cost of land preparation	LPRP	-	-1.91E-06	1.68E-06	-1.136560	0.2590
Labor cost	LBCS	-	3.75E-07	5.86E-07	0.640359	0.5237
Cost of agrochemicals	AGCH	-	2.52E-06	2.67E-06	0.944573	0.3477
Average yield	AYLD	+	-0.006006	0.003330	-1.803652	0.0750
Age of farming units' head	RAGE	+/-	-0.004091	0.003678	-1.112475	0.2692
Cassava farming experience	REXP	+/-	0.009132	0.003450	2.646783	0.0097
Level of education	REDU	+	-0.016458	0.031313	-0.525610	0.6006
Farm size	RFMS	+/-	-0.008875	0.006622	-1.340179	0.1839
Use of fertilizer	FERT	+/-	-0.157621	0.050802	-3.102674	0.0026
Quantity of stems	QSTM	+/-	-0.005897	0.001830	-3.222103	0.0018
Household size	RHHS	+/-	0.002493	0.009345	0.266733	0.7903
R-squared			0.266265	Mean dependent variable		0.643818
Adjusted R-squared			0.167837	S.D. dependent variable		0.263525
S.E. of regression			0.240395	Akaike info criterion		0.105681
Sum squared residual			4.738779	Schwarz criterion		0.430357
Log likelihood			7.032993	F-statistic		2.705183
Durbin-Watson stat			1.914465	Prob(F-statistic)		0.005051

\*\*\*=significant at 1% level; \*\*=significant at 5% level; \*=significant at 10% level; "n/a"=not applicable

Source: Calculated using Field Survey Data