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Optimization of Robust Technical Efficiency in Anchor Borrower Loan Beneficiary Smallholder's Rice Farms in Borno State, Nigeria

Tijani, B. A.
Department of Agricultural Technology, Ramat Polytechnic Maiduguri, Borno State, Nigeria
Email: abiso06@gmail.com

Abstract: *This study estimated and optimized robust technical efficiency in anchor borrower loan beneficiary smallholder's rice farms in Borno State, Nigeria. The target population were anchor borrower loan beneficiary smallholder rice farmers in Borno State, Nigeria. This study relied on primary data that was collected within 2022 rice production year for its analyses. Survey research design was employed to collect data using self-designed structured questionnaire. Multi-stage sampling technique was employed to randomly and proportionately select a total sample size of (300) smallholder rice farmers from (6) LGAs that include Dikwa, Jere, Mobbar, Marte, Shani and Biu in the three (3) senatorial districts – Borno Central, Borno North and Borno South using simple random sampling technique. Analytical tools such as descriptive statistics, DEA, DEA-bootstrap estimator using FEAR Package that was installed in R Software and Tobit regression Model were used. The finding of inputs and output slack indicates that the mean output (paddy rice) slack was 803.81 kilogram per hectare while the mean slack for cultivated area was 0.8122 per hectares while that of rice seed was 3.202 kilogram and mean slack for fertilizer used was 26.537 kilogram. The result further reveals that the mean slack for chemicals used was 2.908 liters while hired labour was 6.176 man-days per hectare and that of family labour was 4.062 man-days per hectare. The result also indicates that the mean non-bias corrected technical efficiency (TE_{VRS}) was 0.7865 while the mean non-bias corrected technical efficiency (TE_{CRS}) was 0.4499 with mean scale efficiency (SE) of 0.5622. The result also indicates that the mean bias-corrected technical efficiency (TE_{VRS}) was 0.73930 while the mean bias-corrected technical efficiency (TE_{CRS}) was 0.39470 with mean SE of 0.52897. Furthermore, the mean bias-estimates under VRS assumption was 0.047280 while the mean bias-estimates under CRS assumption was 0.055140. The result of socio-economic factors that contributes to inefficiency among the anchor borrower loan beneficiary smallholder rice farmers indicates that age of farmers, household size, experience in rice farming and access to credit facilities were negative and significant at 10% while contact with extension workers was positive and significant at 5%. Based on findings of the study, the following recommendations were made: there is need for the anchor borrower loan beneficiary smallholder rice farmers to increase the size of their farm holdings in order to decrease the bias trends and improve their production efficiency; and there is need for the government to improve the quality of extension education program to teach smallholder rice farmers on how to use farm resources efficiently.*

Keywords: *Robust Technical Efficiency, Anchor Borrower Loan Beneficiary, Smallholder's Rice Farms, Borno State, Nigeria*

INTRODUCTION

Nigeria Gross Domestic Product (GDP) at basic constant price (real GDP) grew by 2.27 per cent year-on-year from ₦69.80 trillion in 2018 to ₦71.39 trillion in 2019 compared to 1.91 per cent in 2018 (Asunloye, 2020). The growth was largely due to the agricultural sector's contributions of ₦10.50 trillion, with 25.2 per cent shares of the total GDP respectively in 2019 (Asunloye, 2020). Nigeria is the largest rice producer in Africa. It currently produces about 8 million tons of rice out of the Africa average of 14.6 million tons of rice annually

(Anonymous, 2020). The Federal Government of Nigeria is aiming at 18 million tons of rice production by 2023 (Anonymous, 2020). It is projected that Nigeria's rice consumption will rise to 35million metric tons by 2050, increasing at the rate of 7% per annum due to estimated population growth (Umeh and Adejo, 2019; Central Bank of Nigeria (CBN), 2015). Considering the rate at which the country's population increases, there is the need to match the population increase with food production; hence increase in rice production is one way of realizing this dream.

The CBN launched the Anchor Borrowers' Programme (ABP) in 2015 to make cheap funds accessible to smallholder farmers (SHFs) who produce more than 85% of total farm output in Nigeria. ABP is designed to encourage banks to lend to SHFs to boost paddy rice production. The CBN's current effort was to stimulate local production of rice and other commodities, largely due to the adverse effect of their importation to the nation's foreign reserves. Under the intervention, the CBN has set aside the sum of ₦20billion from the N220billion Micro, Small and Medium Enterprises Development Fund (MSMEDF) for farmers at a single-digit interest rate of 9% (Umeh and Adejo, 2019). The programme seeks to pursue objectives such as, creation of jobs, reduction in food imports and diversification of the economy. The programme aims at creating linkages between over 600,000 smallholder farmers (out-growers) and reputable large-scale processors (off-takers) with a view to increasing agricultural output and significantly improving capacity utilization of integrated mills (Umeh and Adejo, 2019). This study thus estimated and optimized robust technical efficiency in anchor borrower loan beneficiary smallholder's rice farms in Borno State, Nigeria.

Statement of the Problem

Most of the smallholder farmers including the anchor borrower loan beneficiaries that are producing rice in Borno State and the whole country rely on traditional technology with low use of improved input technologies. Currently, the average paddy rice yields per unit area that ranges between 2.0 and 3.0 t/ha in Northern Nigeria are low compared to the recommended yield that ranges from 6.2 to 8.0 t/ha in lowland and 4.0 to 6.0 t/ha in upland (Kamai, Omoigui, Kamara and Ekeleme, 2020). The target paddy rice yield has therefore not been achieved in the Nigeria. This could be due to inputs and output slack among smallholder rice farmers that has not been addressed by earlier studies in the study area. The smallholder rice farmers could possibly increase their output through more efficient use of land, labour, fertilizers and other farm inputs.

The nonparametric linear programming DEA attributes the entire distance from the efficiency frontier to inefficiency. The DEA might not therefore ensure robust anchor borrower loan beneficiary smallholder rice farms technical efficiency estimates, since it is biased by construction. This study thus, decided to employ the standardized levelled DEA-bootstrap to remedy this problem. Since the DEA-bootstrap techniques can mitigate the underlying bias to certain level. Earlier study by Kara (2019), employed DEA to estimate the level of technical efficiency of anchor borrowers′ smallholder rice farmers in Kebbi State, Nigeria. His findings were biased, due to the fact that the DEA estimator produces a biased technical efficiency scores of the frontier. To the best of the researchers knowledge there is no existing study that applied standardized levelled DEA-bootstrap to estimate and optimize robust technical efficiency in anchor borrower loan beneficiary smallholder rice farms in Borno State, Nigeria. It is against this background that this study was conceptualized to estimate and optimize robust technical efficiency in anchor borrower loan beneficiary smallholder's rice farms in Borno State, Nigeria to increase smallholder rice farmers output and bridge the gap in existing literature in the study area.

Objectives of the Study

The main objective of the study was to estimate and optimize robust technical efficiency in anchor borrower loan beneficiary smallholder's rice farms in Borno State, Nigeria. The specific objectives were to:

i. estimate inputs and output slacks of the anchor borrower loan beneficiary smallholder's rice farms;

ii. estimate the robust technical efficiency level of the anchor borrower loan beneficiary smallholder rice farms; and

iii. determine the socio-economic factors that contributes to inefficiency among the anchor borrower loan beneficiary smallholder rice farmers.

Research Hypothesis

The following hypotheses were postulated for testing:

i. H_0: the socio-economic factors have not significantly contributed to inefficiency among the anchor borrower loan beneficiary smallholder rice farmers; and

ii. H_a: the socio-economic factors have significantly contributed to inefficiency among the anchor borrower loan beneficiary smallholder rice farmers.

LITERATURE REVIEW

Empirical Studies on Efficiency

Ayuba, Abba and Abubakar (2020) examine the effect of anchor borrowers programme (ABP) on technical efficiency of beneficiary rice farmers in Kebbi State, Nigeria. A multi-stage sampling technique was used to collect data from total sample size of 1000 beneficiary and non-beneficiary rice farmers. They analyzed the data using stochastic frontier production function. The findings from technical efficiency estimates showed that the beneficiary rice farmers had mean value of 0.91 while the non-beneficiary farmers had mean value of 0.79 The study further indicated that although both categories of farmers were inefficient in the use of existing resources, the ABP beneficiaries are more technically efficient suggesting that ABP enhanced the technical efficiency of the beneficiary farmers. The results also showed that for the beneficiary rice farmers, age was significant and positively related to technical efficiency while educational level, farming experience, membership of cooperative, seed variety, planting technology and income level had negative relationship with technical efficiency. The findings for non-beneficiary farmers indicated that age had positive relationship with technical efficiency whereas educational level, farming experience, membership of cooperative, seed variety, planting technology and income level had negative relationship with technical efficiency.

Okeke, Mbanasor and Nto (2019) conducted comparative analysis of the technical efficiency of beneficiary and non-beneficiary rice farmers of the Anchor Borrowers' Programme in Benue State, Nigeria. They employed multi-stage sampling technique to collect primary data using well-structured questionnaire from 768 rice farmers that composed of 388 beneficiaries and 380 non-beneficiaries from 18 communities and 18 Local Government Areas. Data were analyzed using descriptive statistics, multiple regression analysis, and stochastic frontier production function. Their result indicated that the beneficiary rice farmers achieved lower levels of technical efficiency compared to the non-beneficiary rice farmers and that seed (0.483) and agrochemical (1.60) used, increased technical efficiency more among beneficiary rice farmers than the non-beneficiary rice farmers whereas fertilizer (-1.285) used, decreased technical efficiency of beneficiary rice farmers more compared to the non-beneficiary rice farmers. The results further showed that rice production among the beneficiaries was in stage I of the production curve and that gender (1.249), educational level (-0.045), age (0.058), membership of cooperative (-0.250), extension visit (0.126), marital status (-2.633), and household size (0.059) significantly influenced their technical inefficiency.

Kara (2019) examine the effects of anchor borrowers′ programme on smallholder rice production risk and technical efficiency in Kebbi State, Nigeria. Data were collected from a total of 222 loan beneficiaries and 155 non-beneficiaries farmers using cluster sampling technique. The study employed translog stochastic frontier model with flexible risk properties to estimate efficiency levels while taking into account production risk. Data Envelopment Analysis (DEA) was also used to estimate the level of technical efficiency without accounting for production risk. The finding indicates the presences of technical inefficiency and production risk. Inputs such as seed, fertilizer, agrochemicals, and labour positively affect rice production for both beneficiaries and non-beneficiaries. The result also showed that beneficiary's farms in research region indicated increased scale yields while non-beneficiaries decrease scale yields. Fertilizer and agrochemicals reduce the risk of output for beneficiaries, likewise seed, and labour reduce risk of output for non-beneficiaries. The mean technical efficiency estimated with flexible risk element was 85.3% while without risk element was 65.5% for beneficiaries. Whereas the mean technical efficiency estimated with flexible risk element was 77.6% while without risk element was 56.7% for the non-beneficiaries.

Umeh and Adejo (2019) assessed Central Bank of Nigeria's anchor borrowers' programme effects on rice farmers in Kebbi State, Nigeria. They used primary and secondary data. The primary data were collected through questionnaire from 226 rice farmers (113 beneficiaries and 113 non-beneficiaries of ABP), while the secondary data included annual time series data on Nigeria's rice import quantity and cost (1990-2016). Analytical tools employed included descriptive and inferential statistics. The findings indicated fluctuations in trend of Nigeria's rice import quantity and cost. The beneficiaries were 17% more efficient with mean technical efficiency of 0.98, compared to the non-beneficiaries with mean technical efficiency of 0.81. This further interpreted to higher mean output (5504.4kg/ha) of beneficiaries, compared to the mean output of 3267.7kg/ha of non-beneficiaries. Linkage proven by ABP was favourable in time and price for the beneficiary farmers. The result also indicated that extension visits, trainings/seminars on farming, increase in income, ready market for produce, employment creation, and improvement on standard of living were other benefits derived by the beneficiaries from ABP in the study area.

Okeke, Mbanasor and Nto (2009) examine the effect of anchor borrowers' programme access among rice farmers in Benue State, Nigeria. They employed multi-stage sampling technique to collect data using structured questionnaires from 768 rice farmers comprising of 388 beneficiaries and 380 non-beneficiaries from 18 communities and 18 Local Government Areas. The data were analysed using independent t-test and endogenous switching regression model (ESRM). The independent t-test results showed that the income and farm output of beneficiaries of anchor borrowers' programme (ABP) were significantly higher compared to the non-beneficiaries. The ESRM result indicated that rice farmers' access to ABP was significantly influenced by their socio-economic characteristics and that beneficiary and non-beneficiary rice farmers were not better or worse in terms of farm income than a random rice farmer from the samples. Furthermore, the ESRM showed that beneficiary rice farmers acquired lesser productive assets than what a random rice farmer from the sample would have earned while non-beneficiary rice farmers acquired more productive assets than what a random rice farmer from the sample would have earned.

Theoretical Framework

Production Theory

In the environments of efficiency estimation based on the production theory, production can be considered as a procedure where farmers make use of a given amount of inputs (represented by input vector x) to produce an amount of output (represented by y) (Hokkanen, 2014). The farmers transform a given amount of farm inputs into outputs using some technology of production, which could be characterized either by set-theoretic notions or the accustomed production function method. The explanation of production theory can begin by introducing the sets of input and output along with the technology set for a particular production technology. The set of technology Ψ can be well-described as the set of achievable production systems, which could be produced with definite technology of production particular to the unit of production observed (Hokkanen, 2014): This can be expressed as follows:

$$\Psi = \{(y, x) : x \text{ , this can yield } y\}$$

The border of this set is instinctively the production frontier, which re-counts maximum output producible for any given input vector. The sets of input of the same production technology are therefore described as the sets of inputs vector that are achievable for each component of the output vector y .

$$\varphi(y) = \{x : (y, x) \in \Psi\}$$

Also, the border of this set forms isoquants of the input for the technology of production. Lastly, the output set can be described as the set of achievable outputs, for every likely input vector x.

$$\rho(x) = \{y : (y, x) \in \Psi\}$$

Correspondingly to the sets described above, the border of the output set describes isoquants of the output for a particular output y .

Standardized Levelled DEA-bootstrap Technique

Efficiency estimation based on DEA-bootstrap estimator proposed by Simar and Wilson (1998), consist of repeated simulation of Data Generating Process (DGP) through re-sampling the surveyed data set. DEA-bootstrapping therefore comprises re-sampling the original data by means of reiterating it many times through adjustment of the DGP to generate new or pseudo spurious data. The method of bootstrapping fundamentally involves a Monte Carlo test which is the simplest technique of bootstrap. Gocht and Balcombe (2006), shows that Monte Carlo estimation is used to simulate the DGP to generate valid estimator of the true indefinite DGP. Bootstrap creates opportunity to examine and ratify whether or not the data set from the observations are biased by stochastic effects through the bias estimates and it has the capability to construct confidence interval for bias-corrected estimates which would have been otherwise impossible be derived systematically (Gabdo, Abdlatif, Mohammed and Shamsuddin, 2014a; Gocht and Balcombe, 2006). The concept of bootstrapping is based on lack of statistical property of the DEA estimator which leads to biased DEA estimates and thus bogus result (Hoang-Linh, 2012).

According to Simar and Wilson (2000) and Halkos and Tzeremes (2010), the limitations of the DEA can be taken care by bootstrapping which is at present the best viable method for instituting a reliable statistical property of the DEA estimator. Hence, subjecting the DEA estimates to additional estimation to achieve a more consistent and robust DEA scores by means of bootstrapping. The variance between the bootstrapped DEA and original DEA is regarded as the error term (Simar and Wilson, 1998). The bootstrapped DEA efficiency estimates are assumed to be independently distributed and are only generated by correcting the input vectors to create new DEA efficiency estimates (Hoang-Linh, 2012). The technique of bootstrapping is easy and applied quickly and produces consistent efficiency scores. Its bias correction is captured by the variance between the original scores and mean of the bootstrapped replications. Given the efficiency of a unit point estimate $\{x_\kappa, y_\kappa\}$ denoted as $\theta_\kappa = \left[\dfrac{\theta}{\theta_{x\kappa}} \subset X(y_\kappa)\right]$, where: $X(y_\kappa)$ = set of input bundles. Assume θ_κ= 1, unit κ turn out to be apparently input efficient. In order to attain full efficiency as in the earlier condition, for values of $\theta_\kappa \leq 1$, varying level of input reduction on the unit κ is achievable. In their study, Simar and Wilson (1998) indicated y_κ as the efficient input level corresponding to the output level. Therefore, y_κ as $x^\theta = (\dfrac{x_\kappa}{y_\kappa}) = \theta_\kappa x_\kappa$. The θ_κ here denotes radial measure of distance between x_κ and y_κ, and the corresponding frontier. The variable of interest is θ_κ, which would be estimated and till estimated it remains indefinite since, both $X(y)$ and $\theta_\kappa x_\kappa$ are also indefinite.

Technique of Data Generating Process

The data generating process (DGP) method as explained by Gocht and Balcombe (2006), was that ρ in the DGP set up, generates random sample $X = (x_\kappa, y_\kappa, \kappa = 1,2,......,n)$. By applying a non-parametric method on the X data yields the expression:

$$\hat{\theta}_\kappa = \min\left[\theta \middle| y_\kappa \leq \sum_{i=1}^{n} y_i y_i \middle| \theta_{x\kappa} \geq \sum_{i=1}^{n} y_i x_i \middle| \sum_{i=1}^{n} y_i = 1, y_i \geq 0 \middle|\; \theta \geq 0 \middle| i = 1,2,....,n\right]$$

The efficiency estimation $\hat{\theta}_{\kappa} = \min\left[\theta \middle| \theta_{x\kappa} \subset \hat{X}(y_{\kappa}) \right]$ aids to acquire $\hat{X}$ and $\partial X(y)$. As in the DGP and is indefinite, the method of bootstrap aids to acquire DGP ρ as an important estimator of the correct indefinite DGP achieved through the data $\hat{\rho}$. The estimates of efficiency are regarded as original population and serves as a source from which quasi data or original data set $X^{*} = \left[x_i^{*} y_i^{*}, i = 1,2,....,n\right]$ are haggard. The quasi data can forecast the corresponding amounts $\hat{X}^{*}(y)$ and $\partial \hat{X}^{*}(y)$. Take note that, these forecasts are conditional on X and since $\hat{\rho}$ is known, $\hat{X}^{*}(y)$ and $\partial \hat{X}^{*}(y)$ are too known. The Monte Carlo estimation is used to achieve the sampling distribution by forecasting $\hat{\rho}$ to create B quasi samples x_b^{*}, where b=1… B and quasi estimates of the efficiency values. It's apparent that $\hat{\rho}$ could be analytically difficult to calculate. The distribution of quasi approximations empirically estimates for the unknown sampling distribution of the efficiency values.

Choice of Bootstrap Technique and Stages Involved in the Chosen Technique

The naive bootstrap generates inconsistent estimates (Gocht and Balcombe, 2006), and that the standardized levelled bootstrap technique proposed by Simar and Wilson (1998) is an easily implementable algorithm which generates, consistent bootstrap values from kernel density estimates and the very wide application of the standardized levelled bootstrap technique in the field of agriculture are perhaps the justification for the choice and application of the standardized levelled bootstrap technique in estimating technical efficiency among the anchor borrower loan beneficiary smallholder rice farmers in Borno State, Nigeria. The stages involved in the standardized levelled bootstrap estimator following Gabdo *et al.* (2014a) are:

Given input/output data as $\{x_{\kappa} y_{\kappa}\}$ and any DMU (anchor borrower loan beneficiary smallholder rice farms) as κ. If $\kappa = 1,2,3,....,n,$ to obtain the efficiency estimators, calculate $\hat{\theta}_{\kappa}$ by means of linear programming. The linear model specifications are different estimators of the same indefinite θ_{κ} in this case. Therefore, $\hat{\theta}_{\kappa}$ estimator denote random variables and normally a particular realization of different random variables.

The levelled bootstrap sample $\theta_1^{*}, \theta_2^{*}, ..., \theta_n^{*}$ for i=1, 2,…,n are created by constructing $\beta_1^{*}, \beta_2^{*}, ..., \beta_n^{*}$ a simple bootstrap sample derived by drawing with replacement. A random sample size can therefore be obtained as:

$$\tilde{\theta}_i^{*} = \begin{bmatrix} \beta_i^{*} + \eta\varepsilon_i^{*} & if \beta_i^{*} + \varepsilon_i^{*} \leq 1 \\ 2 - \beta_i^{*} - \eta\varepsilon_i^{*} & otherwise \end{bmatrix}$$

The corrected bootstrap sample is then obtained through:

$$\theta_i^* = \bar{\beta}^* + \frac{1}{\left[\frac{\sqrt{1+\eta^2}}{\hat{\partial}^2_{\hat{\theta}}}\right]\left(\tilde{\theta}_1^* - \bar{\beta}^*\right)}$$

Where: the sample variance of $\theta_1^*, \theta_2^*, ..., \theta_n^*$ is represented by $\bar{\beta}^* = \frac{1}{n\sum_{i=1}^{n}\beta_i^*}$, $\hat{\delta}^2_{\tilde{\theta}}$ while the bandwidth factor is η and the random deviate is ε_i^*. The calculation of bandwidth factor following Simar and Wilson (1998), recommended the use of normal reference rule and set the bandwidth $\eta = 1.06\hat{\delta}^2_{\tilde{\theta}}\, n^{-1/5}$ as for a normally distributed data set $(\hat{\theta})$. In addition, Simar and Wilson (1998) proposed the application of least square cross confirmation that depend on selection of bandwidth that minimizes an estimate to mean integrated square errors for non-normally distributed data set. Efficiency estimation via DEA approach, being a non-normally distributed data set, requires application of the second method. The least square cross confirmation approach was therefore used in this study.

Using the levelled bootstrap sample sequences previously to calculate the new data

$x_b^* = \left[(x_b^*, y_i) \middle| i = 1,2,3,....., n\right]$ where: $x_{ib}^* = \left(\hat{\theta}_i \big/ \theta_{ib}^*\right) x_i, \left[i = 1,2,3,...., n\right]$

To end with, calculate the estimates of the bootstrap efficiency $\left[\hat{\theta}_i^* \middle| i = 1,2,3,...., n\right]$. In order to solve the DEA model for each of the anchor borrower loan beneficiary smallholder rice farms, the bootstrap efficiency estimate was computed by using the new data x_b^*. For a particular anchor borrower loan beneficiary smallholder rice farm, $\kappa = 1$ for instance is shown as: the estimates of the bootstrap $\hat{\theta}_{ib}^*$ could be done by solving the model:

$$\hat{\theta}_{\kappa,b}^* = \min\left(\theta > 0 \middle| y_\kappa \le \sum_{i=1}^{n} y_i y_i \middle| \theta_{x\kappa} \ge \sum_{i=1}^{n} y_i x_{i,b}^* \middle| \sum_{i=1}^{n} y_i = 1, y_i \ge 0, i = 1,..., n\right)$$

To provide for $\kappa = 1,2,3,...., n$ a set of estimates $\left(\hat{\theta}_{\kappa,b}^*\; b = 1,2,3,..., B\right)$, stages a) to d) above are repeated B times. A minimum of 2000 bootstrap iterations were recommended by Simar and Wilson (1998), and was adopted in this study, where B was also set at 2000. The DEA efficiency scores $\hat{\theta}_\kappa$ and the bootstrap efficiency scores $\hat{\theta}_\kappa^*$ denotes approximations to θ_κ and $\hat{\theta}_\kappa$ respectively.

The Bootstrap Bias Estimation

The variance between the original efficiency point estimates (non-bias corrected efficiency estimates) and the new bootstrap efficiency estimates (bias-corrected efficiency estimates) is known as bias estimates (Gabdo, Abdlatif, Mohammed & Shamsuddin, 2014b). The estimate of bootstrap $\left(\hat{\theta}^{*}_{\kappa,b}\; b = 1,2,3,...,B\right)$ is represented by biased (Simar and Wilson, 1998). The bootstrap technique that was used to obtain the bias estimate can be expressed as: $BIAS\left[\hat{\theta}_{\kappa}\right] = E\left[\hat{\theta}_{\kappa}\right] - \theta$

The bootstrap bias for the original estimator $\hat{\theta}_{\kappa}$ is empirically expressed as follows: $BIAS_{B}\left[\hat{\theta}_{\kappa}\right] = B^{-1}\left\{\sum_{b=1}^{B}\hat{\theta}^{*}_{\kappa,b}\right\} - \hat{\theta}_{\kappa}$

The original efficiency estimates minus the bias component yields the bias corrected efficiency estimator. The Farrell's convention was employed in this study where the bias estimates would be positive. For the Sheppard's distance function, the bias estimates may at times be negative.

The Confidence Interval Estimation

Four (4) categories of confidence interval that includes; a) Efron percentile interval (Efron, 1979), b) Hall percentile interval based on difference, c) Efron's bias corrected intervals (Efron, 1979) and d) percentile intervals based on ratios were proposed by Simar and Wilson (1998). This study adopted the Hall percentile interval based on differences due to its simplicity (Atkinson and Wilson, 1995). Generally, confidence interval was built for the bootstrapped scores or bias corrected efficiency estimates of every individual anchor borrower beneficiary smallholder rice farm, κ.In a situation the distribution of $\left\{\hat{\theta}^{*}(x,y) - \theta(x,y)\right\}$ is known at that point chance abounds for finding a_a, b_b in such that:

$$\rho_r\left[-b_a \le \hat{\theta}_{\kappa}(x_0, y_0) - \theta(x_0, y_0) \le -a_a\right] = 1 - a.$$

As, a_a and b_a are indefinite terms, scholars apply $\left(\hat{\theta}^{*}_{\kappa,b}\; b = 1,2,3,...,B\right)$ to forecast them as $\hat{a}_a$ and $\hat{b}_a$ therefore scholars get: $r\left[-\hat{b}_a \le \hat{\theta}^{*}_{\kappa,b}(x_0, y_0) \le \hat{a}_a \middle| \hat{\rho}(X_a)\right] = 1 - a$

Forecasting $\hat{a}_a$ and $\hat{b}_a$ suggests sorting values as $\hat{\theta}^{*}_{\kappa,b}(x_0, y_0) - \hat{\theta}_{\kappa}(x_0, y_0), b = 1,2,3,.....,B$ in sequential order and erasing $\left\{\left(a/2\right)X100\right\}^{\%}$ of rows at each end of the list and setting $-\hat{b}_a$ and

$-\hat{a}_a$ to the extreme points of the array with $\hat{a}_a \leq \hat{b}_a$. The confidence interval $(1-a$ percent) now turn out to be:

$$\hat{\theta}_\kappa = \{x_0, y_0\} + \hat{a}_a \leq \theta\{x_0, y_0\} \leq \hat{\theta}_\kappa\{x_0, y_0\} + \hat{b}_a$$

In order to derive n confidence interval for any given anchor borrower beneficiary smallholder rice farm, this procedure was simulated n times.

METHODOLOGY

Study Area

Borno State is one of the largest states in Nigeria, covering a total land area of 69,435 square kilometer, about 7.67% of the total land area of the country (Ministry of Land and Survey, 2019). The state lies approximately between latitude $10^0$02'N and $13^0$04N and between longitudes $11^0$04^{0}E and $14^0$04E (Ministry of Land and Survey, 2019). It shares boundaries with Adamawa State to south Gombe State to South east and Yobe State to the east. It also shares International boundaries with the Republic of Chad northwest and Cameroon to the southwest. According to the 2006 census figures, Borno State has a population of 4, 151,193 with a population density of approximately 60 persons per square kilometer (National Population Commission (NPC), 2006). The state is presently structured into 27 Local Government Areas that include: Maiduguri, Jere, Bama, Gowza, Kala Balge, Ngala, Mafa, Marte, Monguno, Guzamala, Bayo, Kuya Kusar, Biu, Shani, Kaga, Askira Uba, Hawul, Gubio, Kukawa, Abadam, Mobbar, Magumeri, Nganzai, Konduga,

The State, which is predominantly agrarian, is characterized by three natural agro-ecological zones which include the Sahel savannah in the extreme north, the Sudan savannah in the central part and the northern Guinea Savannah in the southern part (Folorunsho, 2006). The climate of the area is characterized by dry and wet season. The wet season lasts from March to October, while the dry season is from October to April. The average annual temperature is about 30^0C with a maximum of 45^0C in March and a minimum of 15^0C during the dry harmattan season. The annual rainfall ranges from 400mm to 700mm in the north and 500mm to 900mm in the southern part (Folorunsho, 2006). The soil types are clay, sandy loam, clay loam, sandy etc. With common weeds such as Sudan grass, spear grass *pennisetum spp*, gamba grass *striga spp* etc, with herbs and shrubs. Major crops grown in the area include millet, sorghum, groundnut, rice, wheat, cowpea bambaranut, etc. Vegetables such as tomatoes, okro, onion, pepper, etc. and livestock such as cattle, sheep, goat, pigs, camel, horse and donkey. The major occupations of people in the area are farming, cattle rearing and fishing. The principal ethnic groups are kanuri, Shuwa/Arab, Bura, Marghi, and Gwoza. Others include Fulani, Hausa, etc.

Research Design

The research design used in this study was the survey research design. In which self-developed structured questionnaire was used during the survey process to collect reliable data from the anchor borrower loan beneficiary smallholder rice farmers in Borno State, Nigeria.

Sampling Technique

Multi-stage sampling technique was employed for this study. In the first stage, all the three (3) senatorial districts – Borno Central, Borno North and Borno South – were selected. Two (2) accessible major rice producing Local Government Areas (LGAs) were purposively selected from each of the (3) senatorial districts, in the second stage. These LGAs include Dikwa, Jere, Mobbar, Marte, Shani and Biu LGAs, making a total of six (6) LGAs for the study. While in the third stage, five (5) major rice producing wards were randomly selected from each of the (6) LGAs, making a total of (30) wards for the study. Finally, a total sample size of (300) anchor borrower loan beneficiary smallholder rice farmers were randomly and proportionately selected using simple random sampling technique from the list of beneficiary smallholder rice farmers that was obtained from CBN in the (30) wards and used for the analysis.

Population for the Study

The target population for this study were anchor borrower loan beneficiary smallholder rice farmers in 30 wards of Dikwa, Jere, Mobbar, Marte, Shani and Biu LGAs across the three (3) senatorial districts – Borno Central, Borno North and Borno South of Borno State, Nigeria.

Sample Size for the Study

A sample size of (300) anchor borrower loan beneficiary smallholder rice farmers were randomly and proportionately from the 30 wards of Dikwa, Jere, Mobbar, Marte, Shani and Biu LGAs across the three (3) senatorial districts of Borno State using simple random sampling technique. According to Krejcie and Morgan (1970) and Yamane (1967), a sample size of 300 respondents is adequate for a study of this nature. The formula for the determination of the sample size is therefore expressed as:

$$n = \frac{N}{1 + N(e)^2}$$

Where:

n = Sample size

N = Population size (sample frame)

e = Level of significance = 5%

1 = constant

Sources of Data

Data for the study were collected from both primary and secondary information sources. The primary data were collected using self-developed structured questionnaire that was designed and administered to (300) anchor borrower loan beneficiary smallholder rice farmers in the study area. The secondary sources of information included journal, bulletins, textbooks, internet, conference papers, past projects, dissertation etc.

Method of Data Collection

Primary data was collected through the use of self-developed structured questionnaire via face-to-face interview. The questionnaire were administered by the researcher alongside trained enumerators (extension agents) of Agricultural Development Programme (ADPs) in the selected LGAs in Borno State. Qualitative information were also recorded from the selected anchor borrower loan beneficiary smallholder rice farmers with a view to having the right output from the survey work. To ensure validity of the data, information were triangulated through conducting discussions with extension agents and other staff of the zonal agricultural offices in the States.

Pilot Study

The survey instruments were subjected to pilot study by administering it on the 30 anchor borrower loan beneficiary smallholder rice farmers considered for the study to ascertain the quality, adequacy and usability of the survey instruments; use the findings of the pilot study to fine-tune the survey instruments; and cross-check the adequacy of field arrangements and logistics.

Analytical Technique

Analytical tools used for this study includes descriptive statistics, DEA, DEA-Bootstrap estimator and Tobit regression Model. Descriptive statistics such as frequency, percentage, mean and standard deviation were used to organize and summarize the findings to achieve the specific objectives (i), (ii), and (iii) of the study.

Data Envelopment Analysis (DEA) Model

FEAR Package was installed in R Software to estimate the DEA-Bootstrapped technical efficiency while DEAP Software was employed to estimate the inputs and output slacks. The selection of input or output-oriented DEA model depends on the quantities of inputs or output the anchor borrower loan beneficiary smallholder rice farms have (Coelli, Rao, O'Donnell and Battese, 1998). Since farmers have more control over inputs than output, the researcher therefore employed the input-oriented DEA model. This was used to achieve specific objectives (ii) and (iii). The overall technical efficiency and pure technical efficiency under the assumption of constant returns to scale (CRS) and variable returns to scale (VRS) based on the input -oriented DEA model following Coelli et al. (1998) is stated below. The input-oriented constant return to scale (CRS) is specified as:

$$\text{Min}_{\theta,\lambda}\ \theta$$

Subject to

$$-y_i + Y\lambda \geq 0$$

$$\theta x_i - X\lambda \geq 0$$

$$\lambda \geq 0$$

Where:

Y_j = output matrix for N rice farms

θj = overall technical efficiency of the ith rice farm

λj = N x 1 constraints

Xj = input matrix for N rice farms

y_i = output of the ith rice farm (Total quantity of rice output produced (kg))

xi = input vector of x_{1i}, x_{2i}…….x_{5i} inputs of the ith rice farm

x_{i1} = cultivated area (hectares)

x_{i2} = rice seed (kg)

x_{i3}= fertilizer (kg)

x_{i4} = chemicals (liters)

x_{i5} = hired labour (man-days)

x_{i6} = family labour (man-days)

i = 1, 2, 3, rice farms

The input-oriented variable return to scale (VRS) DEA model for calculation of pure technical efficiency is expressed (Coelli et al., 1998) as:

$$\text{Min}_{\theta,\lambda}\ \theta,$$

Subject to

$$-y_i + Y\lambda \geq 0$$
$$\theta x_i\ X\lambda \geq 0$$
$$N1'\lambda=1$$
$$\lambda \geq 0$$

Where: θ = the pure technical efficiency of ith rice farm, $N1'\lambda=1$ is a convexity constraint which ensured that an inefficient farm was only benchmark against farms of similar size. While the scale efficiency was estimated by dividing the overall technical efficiency (TE_{CRS}) by pure technical efficiency (TE_{VRS}). It is expressed as:

$$SE = TE_{CRS}/\ TE_{VRS}$$

Where:

SE = 1, implies scale efficiency (SE) or constant return to scale (CRS). SE < 1, implies scale inefficiency. The farms scale inefficiency arise due to presence of either increasing returns to scale or decreasing return to scale. This was determined by estimating another DEA model under non-increasing returns to scale (NIRS). Following Coelli, et al. (1998), input oriented (VRS) DEA model under non-increasing returns to scale (NIRS) is expressed as:

$$\text{Min}_{\theta,\lambda}\ \theta,$$

Subject to

$-y_i + Y\lambda \geq 0$

$x_i - X \geq 0$

$N1'\lambda \leq 1$

$\lambda \geq 0$

The study also employed the standardized leveled DEA-bootstrap estimator to estimate the robust technical efficiency estimates of anchor borrower loan beneficiary smallholder rice farms.

Tobit Regression Model

The bias-corrected technical efficiency estimates that was obtained from the solution of the DEA problem at the first stage was subtracted from one and later regressed on the socio-economic factors that contributes to inefficiency of the anchor borrower loan beneficiary smallholder rice farmers at the second stage using a Tobit regression model. The bias-corrected inefficiency scores (dependent variable) was obtained by deducting the technical efficiency scores from one following Ismail (2015), Featherstone et al. (1997) and Tijani *et al.* (2017). This was used to achieve the specific objective (iv). The reduced form of the Tobit regression model is expressed as:

$\text{Technical Ineff}_i = \alpha_0 + \alpha_1 Z_{i1} + \alpha_2 Z_{i2} + \alpha_3 Z_{i3} + \alpha_4 Z_{i4} + \alpha_5 Z_{i5} + \alpha_6 Z_{i6} + \alpha_7 Z_{i7} + \alpha_8 Z_{i8} + \varepsilon_i$

Where:

Technical Ineff_i = inefficiency score for ith anchor borrower loan beneficiary smallholder rice farmer;

α_0 = coefficient of the intercept;

$\alpha_1 - \alpha_8$ = parameters to be estimated;

Z_1 = age of a farmer (years);

Z_2 = educational level (years spent in formal education);

Z_3 = household size (number);

Z_4= experience in rice farming (years);

Z_5= rice farm income (₦);

Z_6 = access to credit facilities (dummy)

Z_7 = contact with extension workers (dummy)

Z_8 = membership of rice smallholder farmers' association (dummy)

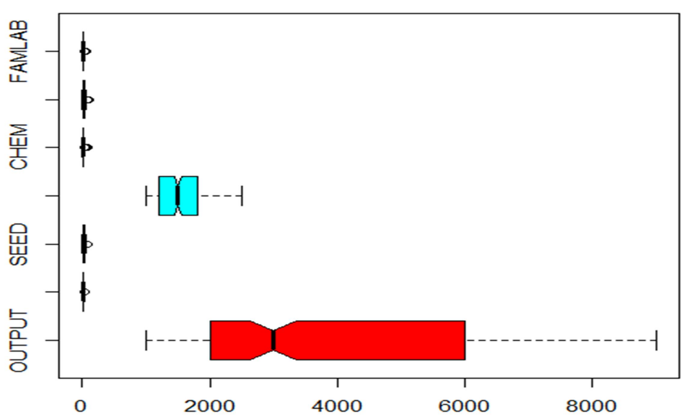
ε = error term

i = 1, 2, 3… N rice farms.

RESULTS AND DISCUSSION

Detection of Outliers in Anchor Borrower Loan Beneficiary Smallholder Rice Farmers Production Data and Diagnostic Statistics

Outlier detection was carried out by employing boxplot to eliminate extreme values in the data used for the analyses in the study. Figure 1 illustrates the boxplot for the anchor borrower loan beneficiary smallholder rice farmer's production data that was plotted after replacing the outliers with their means. This suggests non-existence of extreme values in all the smallholders' rice farms data sets. The boxplots indicates that all the observations in the smallholder's rice farms were within the lower and upper quartile. This further implies that the data sets used for the analyses in this study were free from outliers as revealed in figure 1. The examination of outliers is generally essential as it shows the normality, mean, median, skewness and kurtosis. It is significant particularly in efficiency estimation when using non-parametric techniques like the DEA that are very sensitive to extreme values (Tijani, 2017; Gabdo *et al.,* 2014b; Gocht and Balcombe, 2006).



Source: Computed using field survey, data 2022
Figure 1: Outliers Detection in Anchor Borrower Loan Beneficiary Smallholder Rice Farmers Production Data

Summary Descriptive Statistics of the Data used for the Analyses

The finding of summary of descriptive statistics of the data used for the analyses in table 1 indicates the statistical behaviuor of the anchor borrower loan beneficiary smallholder farms data used for the study.

Table 1: Summary Descriptive Statistics of Variables used for the Analyses

Variables	Mean	Standard deviation	Minimum	Maximum
Paddy Rice (kilogram)	4,153.33	2365.504	1,000	9,000
Cultivated area (hectare)	16.82	6.533	10	35
Rice seed (kilogram)	27.67	16.542	3	90
Fertilizer (kilogram)	1,572	449.693	1,000	2,500
Chemicals (liters)	12.94	11.787	3	90
Hired labour (man-days)	34.97	23.543	6	97
Family labour (man-days)	16.53	15.235	2	70

Source: Field survey data, 2022

The mean output (paddy rice) was 4,153.33 kilogram per hectare while mean cultivated area was 16.82 hectares. The result also indicates that the mean rice seed was 27.67 kilogram per hectare while mean fertilizer used was 1,572 kilogram per hectare. Furthermore, the mean chemicals used was 12.94 liters, hired labour (34.97 man-days) and family labour (16.53 man-days).

Inputs and Output Slacks of Anchor Borrower Loan Beneficiary Smallholder Rice Farms based on DEA Estimator

The mean output slack shows the deficit or shortfall in output (paddy rice) relative to the best practice anchor borrower loan beneficiary smallholder farms whereas the mean inputs slack reveals the amount by which the inputs were on average, overly used compared to best practice smallholder rice farms. The summary of inputs and output slacks estimates of anchor borrower loan beneficiary smallholder farms in table 2 indicates that the mean output (paddy rice) slack was 803.81 kilogram per hectare while the mean slack for cultivated area was 0.8122 per hectares while that of rice seed was 3.202 kilogram and mean slack for fertilizer used was 26.537 kilogram.

Table 2: Estimates of Inputs and Output Slacks of Anchor Borrower Loan Beneficiary Smallholder Rice Farms based on DEA Estimator

Output /Input	Min. Slack	Max. Slack	Mean Slack	Std. Dev.	Mean Output obtained/Mean Input used	Percentage (%) of Output Shortfall /Excess Input used
Paddy Rice (kilogram)	0.00	5739.69	803.81	1228.42	4,153.33	19.35
Cultivated area (hectare)	0.00	9.13	0.8122	1.758	16.82	4.83
Rice seed (kilogram)	0.00	34.58	3.202	6.916	27.67	11.57
Fertilizer (kilogram)	0.00	724.33	26.537	89.832	1,572	1.69
Chemicals (liters)	0.00	37.71	2.908	6.1223	12.94	22.47
Hired labour (man-days)	0.00	58.65	6.176	11.9983	34.97	17.66
Family labour (man-days)	0.00	57.53	4.062	9.6385	16.53	24.57

Source: Computed field survey data, 2022

Table 2 further reveals that the mean slack for chemicals used was 2.908 liters while hired labour was 6.176 man-days per hectare and that of family labour was 4.062 man-days per hectare in the study area. This implies that compared to the best performing anchor borrower loan beneficiary smallholder farms, the farmers had on the average over-utilized their farm resource on cultivated area by 0.8122 per hectares, rice seed by 3.202 kilogram per hectare, fertilizer by 26.537 kilogram per hectare, chemicals by 2.908 liters per hectare, hired labour by 6.176 man-days per hectare and family labour by 4.062 man-days per hectare in the study area. This also indicates the extent of excess input used or overcrowding which its decrease would not have any effect on the amount of output (paddy rice) and these excess can be shifted to other useful farming options. In order to attain 100% efficiency level in rice production, the anchor borrower loan beneficiary smallholder farms can reduce cultivated area by 4.83%, rice seed by 11.57%, fertilizer by 1.69%, chemicals by 22.47%, hired labour by 17.66%, family labour 24.57% per hectare. The finding also shows that the minimum paddy rice slack of 0.00 while the maximum was 5,739.69 kilogram per hectare with a mean of 803.81. This suggests that relative to the best practice anchor borrower loan beneficiary smallholder rice farms experienced output (paddy rice) shortfall of 5,739.69 kilogram per hectare. On the other hand, the anchor borrower loan beneficiary smallholder rice farms had the prospects of achieving more paddy rice output to the limit of 5,739.69 kilogram per hectare in the study area.

Optimization of Technical Efficiency Level of the Anchor Borrower Loan Beneficiary Smallholder Rice Farms using Robust Standardized Leveled DEA-bootstrap

The robust standardized leveled DEA-bootstrap for the optimization of technical efficiency of anchor borrower loan beneficiary smallholder rice farms was estimated and results of the estimates are presented based on simulation method generated by replicating the original data 2000 times following Simar and Wilson (2007).

Table 3: Estimated Result of Non-bias corrected Technical Efficiency Level of the Anchor Borrower Loan Beneficiary Smallholder Rice Farms based on DEA-bootstrap Estimator under VRS and NIRTS Assumptions

Efficiency Level	Non-bias corrected TE_{VRS}	Non-bias corrected TE_{CRS}	Non-bias corrected TE NIRTS	SE
0.0000-0.2500	0(0.00)	85 (28.33)	85 (28.33)	48 (16)
0.2501-0.5000	19 (6.33)	95 (31.67)	95 (31.67)	96 (32)
0.5001-0.7500	116 (38.67)	70 (23.33)	70 (23.33)	60 (20)
0.7501-0.9999	80 (26.67)	32 (10.67)	32 (10.67)	72 (24)
Fully Efficient (Exactly 1.0000)	85 (28.33)	18 (6)	18 (6)	24 (8)
Total	**300 (100)**	**300 (100)**	**300 (100)**	**300 (100)**
Summary				
Minimum	0.4000	0.0658	0.0658	0.1328
Maximum	1.0000	1.0000	1.0000	1.0000
Mean	0.7865	0.4499	0.4508	0.5622
Sub-optimal(IRTS)				276(92)
Optimal (CRS)				24(8)

Source: Computed using field survey data, 2022, *Figures in parentheses represents percentage of Anchor Borrower Loan Beneficiary Smallholder Rice Farms

The finding of non-bias corrected technical efficiency (TE_{VRS}) of the smallholder rice farms in table 3 based on VRS assumption ranges from 0.4000 to 1.0000 with a mean TE score of 0.7865. The mean non-bias corrected TE_{VRS} suggests 78.65% efficiency level for the anchor borrower loan beneficiary smallholder rice farms with 21.35% inefficiency level. The non-bias corrected technical efficiency (TE_{CRS}) of the smallholder rice farms in table 3 based on CRS assumption ranges from 0.0658 to 1.0000 with a mean TE score of 0.4499. This implies 44.99% efficiency level for the smallholder rice farms with 55.01% inefficiency level. The scale efficiency (SE) of the smallholder rice farms in table 3 ranges from 0.1328 to 1.0000 with a mean SE score of 0.5622. This suggests 56.22% scale efficiency with 43.78%

inefficiency level among the anchor borrower loan beneficiary smallholder rice farms. The nature of return to scale indicates that 92% of the smallholder rice farms operates at sub-optimal (increasing return to scale) of production while only 8% operates at optimal (constant return to scale) of rice production.

Table 4: Estimated Result of Bias-corrected Robust Technical Efficiency Level of the Anchor Borrower Loan Beneficiary Smallholder Rice Farms based on DEA-bootstrap Estimator under VRS and NIRTS Assumptions

Efficiency Level	Bias-corrected TE_{VRS}	Bias-corrected TE_{CRS}	Bias-corrected TE NIRTS	SE
0.0000-0.2500	0(00)	106 (35.33)	110 (36.67)	54 (18)
0.2501-0.5000	28 (9.33)	92 (30.67)	103 (34.33)	99 (33)
0.5001-0.7500	126 (42)	63 (21)	69 (23)	58 (19.33)
0.7501-0.9999	146 (48.67)	39 (13)	18(6)	86 (28.67)
Fully Efficient (Exactly 1.0000)	0(00)	0(00)	00 (00)	3 (1)
Total	**300 (100)**	**300 (100)**	**300 (100)**	**300 (100)**
Summary				
Minimum	0.39160	0.05886	0.05886	0.11998
Maximum	0.99270	0.86470	0.79470	1.0000
Mean	0.73930	0.39470	0.38160	0.52897
Sub-optimal(IRTS)				297(99)
Optimal (CRS)				3(1)

Source: Computed field survey data, 2022, *Figures in parentheses represents percentage of Anchor Borrower Loan Beneficiary Smallholder Rice Farms

Table 4 indicates that the bias-corrected technical efficiency (TE_{VRS}) based on VRS assumption ranges from 0.39160 to 0.99270 with a mean efficiency score of 0.73930. The mean bias-corrected TE_{VRS} efficiency score suggests 73.93% efficiency level with 26.07% inefficiency of the smallholder rice farms. The mean bias-corrected TE_{VRS} concludes that the anchor borrower loan beneficiary smallholder rice farmers can on the average withdraw the usage of inputs quantity by 26.07% and still produce the same level of rice yield provided the production technology and managerial principles of the best practiced smallholder rice farms are employed by all farms (Tijani, 2017; Gabdo *et al.,* 2014b). The bias-corrected technical efficiency (TE_{CRS}) based on CRS assumption ranges from 0.05886 to 0.86470 with a mean efficiency score of 0.39470. The mean bias-corrected TE_{CRS} efficiency score suggests 39.47% efficiency level with 60.53% inefficiency of the smallholder rice farmers.

The scale efficiency (SE) in table 4 ranges from 0.11998 to 1.0000 with a mean score of 0.52897. This suggests the existence of 52.89% scale efficiency level and 47.11% inefficiency among the anchor borrower loan beneficiary smallholder rice farms. The nature of return to scale indicates that 99% of the smallholder rice farms operates at sub-optimal (increasing return to scale) of production while only 1% operates at optimal (constant return to scale) of rice production.

The mean bias-corrected TE_{VRS} based on VRS assumption 0.73930 was higher than the SE of 0.11998. This implies that main cause of technical inefficiency generally seems to be more of scale associated than technical matters like managerial ability (Tijani, 2017; Gabdo *et al.,* 2014b). The finding further suggests that smallholder rice farmers can attain technical efficiency by increasing size of their farm holdings. This was expected *a priori* due to the anchor borrower loan beneficiary smallholder rice farm's small-scale nature who cultivates a small number of hectares together with the DEA-bootstrap's assumption of zero frontiers justified the finding (Tijani, 2017).

Table 5: Estimated Result of Bias Components of the Anchor Borrower Loan Beneficiary Smallholder Rice Farms based on DEA-bootstrap Estimator under VRS and NIRTS assumptions

Efficiency Level	Bias-estimate TE_{VRS}	Bias-estimate TE_{CRS}	Bias-estimate TE NIRTS
0.0000-0.2500	-	-	-
0.2501-0.5000	-	-	-
0.5001-0.7500	-	-	-
0.7501-0.9999	-	-	-
Fully Efficient (Exactly 1.0000)	-	-	-
Total	**300**	**300**	**300**
Summary			
Minimum	0.006808	0.003322	0.004078
Maximum	0.189200	0.0219300	0.0322000
Mean	0.047280	0.055140	0.069180

Source: Computed using field survey data, 2022

The bias estimates of the anchor borrower loan beneficiary smallholder rice farms in table 5 were estimated by subtracting the bias-corrected technical efficiency estimates from the non-bias corrected technical efficiency estimates following Tijani (2017) and Gabdo (2014). Apart from the simulation effect, the conventional DEA technique was used to estimate the non-bias corrected technical efficiency (TE_{VRS}) of the anchor borrower loan beneficiary smallholder rice farms with the noise constituent not implanted while the bias-corrected technical efficiency (TE_{VRS}) accounts for noise which tallies with the bias. Hence, the reason for lower scores of the bias-corrected TE under both VRS and CRS assumptions in contrast to the non-bias corrected TE_{VRS} and TE_{CRS} that are higher (Tijani, 2017; Gabdo *et al.,* 2014b). Generally, the bias-corrected TE estimates in table 4 were lower under CRS assumption compared to the estimates under VRS assumption. This also agrees with the theory that the enveloping surface is tighter under CRS assumption than VRS which is loose (Tijani, 2017).

The bias-estimates under VRS assumption in table 5 further indicates that the minimum and maximum bias-estimates of the anchor borrower loan beneficiary smallholder rice farms were 0.006808 and 0.189200 respectively with a mean of 0.047280. The minimum and maximum bias-estimates of the smallholder farms under CRS assumption were 0.003322 and 0.0219300 with a mean of 0.055140. The bias-estimates were low, meaning the anchor borrower loan beneficiary smallholder rice farms have better protection on factors beyond their control (Tijani, 2017; Gabdo, 2014). The bias-estimates account for factors such as natural disaster, flood, pests and diseases, climate and government policy shocks that are beyond the smallholder rice farmers' control (Tijani, 2017; Gabdo, 2014). In addition, the bias also regulates for best practicing smallholder rice farms not considered in the samples. The bias estimates were lower under CRS assumption compared to that of VRS assumption which also conformed to the theory (Tijani, 2017).

The finding of confidence interval for the bias-corrected technical efficiency under both VRS and CRS assumptions in table 6 indicates that all the bias-corrected efficiency of the anchor borrower loan beneficiary smallholder rice farms scores fall within the minimum and maximum upper and lower bound confidence intervals.

Table 6: Confidence Interval for Bias-corrected Technical Efficiency of the Anchor Borrower Loan Beneficiary Smallholder Rice Farms based on DEA-bootstrap Estimator under VRS and NIRTS assumptions

Efficiency Level	Confidence Interval for Bias-corrected TE_{VRS}		Confidence Interval for Bias-corrected TE_{CRS}		Confidence Interval for Bias-corrected TE_{NIRTS}	
0.0000-0.2500	-		-		-	
0.2501-0.5000	-		-		-	
0.5001-0.7500	-		-		-	
0.7501-0.9999	-		-		-	
Fully Efficient (Exactly 1.0000)	-		-		-	
Total	**300**		**300**		**300**	
Summary						
Limits	**Upper**	**Lower**	**Upper**	**Lower**	**Upper**	**Lower**
Minimum	0.3994	0.3799	0.06481	0.05347	0.06472	0.05390
Maximum	0.9997	0.9776	0.98551	0.79342	0.98634	0.7212
Mean	0.7835	0.6869	0.44110	0.35990	0.44052	0.33890

Source: Computed using field survey data, 2022

Socio-economic Factors that Contributes to Inefficiency among the Anchor Borrower Loan Beneficiary Smallholder Rice Farmers

The socio-economic factors that contributes to inefficiency among the anchor borrower loan beneficiary smallholder rice farmers were estimated and the findings are presented in table 7. The coefficients of age of farmers, household size, experience in rice farming and access to credit facilities were negative and significant at 10% while contact with extension workers was positive and significant at 5%. The negative coefficient of age of farmers suggest that old smallholder rice farmers are more likely to be technically efficient than their younger ones. The reason could be due to older smallholder's more years of experience in rice farming than the younger ones and thus likely to be more productive and technically efficient (Tijani, 2017).

The negative coefficient of household size implies that smallholder's rice farmers with large number persons in their household tends to be technically efficient. The reason could be due to availability of family labour for agricultural activities that results in higher yield and profit in rice production. This agrees with the finding of Tijani (2017) who reported that technical inefficiency reduce with increase in number of persons in smallholder farmers household. Whereas the negative coefficient of experience in rice farming suggests that as the rice smallholder farmers experience in farming increases, their technical inefficiency tends to decrease (Onu, Amaza & Okunmadewa, 2000).

Table 7: Socio-economic Factors that Contributes to Inefficiency among the Anchor Borrower Loan Beneficiary Smallholder Rice Farmers

Socio-economic Factors	Estimated Parameters	Coefficients	Standard Error	T-value
Constant	Z_0	0.8420665	0.0553755	15.21***
Age of a farmer	Z_1	-0.0013336	0.0007917	-1.68*
Educational level	Z_2	-0.0012421	0.0038581	-0.32
Household size	Z_3	-0.005899	0.0036609	-1.61*
Experience in rice farming	Z_4	-0.0014197	0.0009015	-1.57*
Rice farm income	Z_5	-4.10e-08	9.10e-08	-0.45
Access to credit facilities	Z_6	-0.0335148	0.0253165	-1.32*
Contact with extension workers	Z_7	0.0500851	0.0206184	2.43**
Membership of rice smallholder farmers' association	Z_8	0.0156793	0.0283568	0.55
Sigma		0.1618471	0.0066249	24.430***
Log Likelihood		118.81892		
Log Likelihood Ratio		15.48 (p-value 0.0505*)		
Pseudo R^2		-0.0697		

Source: Computed using field survey data, 2022, *= Significant at 10%, **= Significant at 5%, *** = Significant at 1%.

The negative coefficient of access to credit facilities suggests that smallholder rice farmers who have more access to credit facilities were likely to be technically efficient than those who do not have access. This suggests that access to credit reduces technical inefficiency in smallholder's rice production. According to Binam, Tonye, Nyambi & Akoa (2004), farmers who have properly taken the advantages of credit facilities would possibly have their capability to adopt new technologies enhance and thus improve their efficiency.

The positive coefficient of contact with extension workers implies that smallholder rice farmers who have obtained services from agricultural extension workers are more likely to be technically inefficient. Although, agricultural extension services and farmer-extension education programs stand significant policy tools for government to increase agricultural output, hitherto, numerous viewers such as Binam *et al.* (2004), reported reasons such as poor performance in the services of extension and informal education methods, owing to administrative ineffectiveness, lacking package plan, and a number of broad weaknesses in-built in publicly operated, staff-intensive, information conveyance methods. In addition, the type of extension services rendered to the oil palm smallholders seems unsatisfactory which would consequently leads to technical inefficiency (Ofori-Bah and Asafu-Adjaye, 2011).

CONCLUSION AND RECOMMENDATION

The study concludes that relative to the best performing rice smallholder farmer, the farmers had on the average over-utilized their farm resource on cultivated area by 0.8122 per hectares, rice seed by 3.202 kilogram per hectare, fertilizer by 26.537 kilogram per hectare, chemicals by 2.908 liters per hectare, hired labour by 6.176 man-days per hectare and family labour by 4.062 man-days per hectare in the study area. In addition, relative to the best practice anchor borrower loan beneficiary smallholder rice farms experienced output (paddy rice) shortfall of 5,739.69 kilogram per hectare.

The study also concludes that optimal productivity among the anchor borrower loan beneficiary smallholder rice farms can be achieved due to the high non-bias corrected technical efficiency levels. The bias constituents also reveals that the smallholder rice farmers were working under production constraints beyond their control. The study also concludes that apart from managerial constraints, the small scale nature of the rice farm holdings appears to be the main source of inefficiency. The study also affirmed that factors such as age of farmers, household size, experience in rice farming and access to credit facilities decrease inefficiency while contact with extension workers increase inefficiency among the anchor borrower loan beneficiary smallholder rice farmers in the study area. Based on findings of the study, the following recommendations were made:

i. There is need for the anchor borrower loan beneficiary smallholder rice farmers to increase the size of their farm holdings in order to decrease the bias trends and improve their production efficiency.

ii. There is need for the government to improve the quality of extension education program to teach smallholder rice farmers on how to use farm resources efficiently.

iii. There is also need for the anchor borrower loan beneficiary smallholder rice farmers to encourage their members to join and participate in association to enable them benefit from the various activities of the association.

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