



COMPARATIVE STUDY ON TECHNICAL EFFICIENCY OF MAIZE PRODUCING FARMS IN NIGERIA

Muhammad Auwal Ahmed

Department of Agricultural Economics and Extension,
Modibbo Adama University of Technology, P. M. B. 2076 Yola, Adamawa State, Nigeria
Corresponding Author's E-mail: auwalyounky@gmail.com Tel.: 08035668276

ABSTRACT

The paper compared the technical efficiency levels of maize farms in Nigeria using data envelopment analysis (DEA) and slacks-based measure (SBM) of efficiency model. Slacks based super-efficiency and ordinary least square models were also used to examine the super-efficient farms and the causes of technical inefficiency in the study area. The mean technical efficiency scores of DEA and SBM models were 0.78 and 0.66, respectively, implying that farmers could increase their corresponding efficiency levels by 22% and 34% with the current inputs level and technology. The findings indicated that there is a statistically significant difference ($P \leq 0.01$). Between the technical efficiency scores of DEA and SBM models as well as the inputs slacks at varying levels of probability. The variation in the efficiency estimates was attributed to the inherent bias nature of DEA model which does not capture the whole aspect of inefficiency. Thus, SBM model gives more accurate and reliable estimates than the conventional DEA and hence it is reliable. Moreover, the results showed that 15 farmers were super-efficient and regarded as those that utilized inputs optimally during production process. The inefficiency analysis revealed that experience, education, extension services and age have significant impact on technical efficiency. Therefore, the study concluded that maize farmers who had many years of experience and are also privilege to meet with extension personnel have tendency to acquire new skills and operate at the optimum efficiency level. The study recommended that super-efficient farmers should be used as a bench-mark by the inefficient ones since they have the ability to use their farm inputs optimally. This can reduce inefficiencies and lead to more output and reduced production costs as well.

Keywords: Data envelopment Analysis, Maize, Slacks-based measure model, Super-efficiency, Technical efficiency.

INTRODUCTION

More than 800 million tons of maize is produced around the world with the United States being the highest (42%) producer. This is followed by China, Brazil, Mexico, Indonesia, Argentina, and France, respectively (Food and Agriculture Organization [FAO], 2015). Maize is one of the Africa's foremost food crops with more than 50% of the countries assigning over 50% of their cereal crop production area to it. The crop is an important staple food for more than 1.2 billion individuals in Sub-Saharan Africa and Latin America and a major feed constituent in Asia (Ibrahim *et al.*, 2014). Nigeria produces more than 9 million tons of maize



per annum and hence the largest in Africa (FAO, 2015). The crop covers about 50% of the land area assign for farming and accounts for about 43% of the maize grown in West Africa. Maize has currently turned into a feasible crop which numerous agro-based industries rely on as a primary source of raw material. It is a crop that is easy to process, high yielding, freely manage and comparatively inexpensive than other cereals. Maize can be cultivated across different agro-ecological zones of Nigeria (Ogunbodede and Olakojo, 2001). However, maize output per hectare in Nigeria is estimated at 2.0 metric ton which is less than the projected average of 5.1 metric ton per hectare (Ibrahim et al., 2014). The production is not proportional to the prompt population growth which necessitated the importation of about 812,000 tons of maize at the cost of USD1.1 Million in the year 2014 (FAO, 2015). The shortfall might be related to the circumstance that bulk of the farms (more than 90%) are owned by the smallholders who produce about 70% of the total output in the country (International Food Policy Research Institute [IFPRI], 2009). Despite government's determination to enhance maize production by reinforcement of on-farm research, increase in land areas apportioned to maize, fertilizer subsidy by 25%, the distribution of high quality seeds and seedlings, proper use of improved storage facilities, the rapid response to occurrence of pest infestations and implementation of zero tariffs on imported agrochemicals, maize productivity on farmers' fields remain generally low.

The existing low yield levels in maize could be associated to farmers' level of education and experience, access to credit facilities, inadequate contact with extension staffs, farmers' age, non-farm activities, occurrence of drought and low levels of farms' efficiency. The presence of these shortfalls in efficiency indicates that maize output could be improved without requiring additional inputs and new skills. Therefore, the empirical estimates of technical efficiency become crucial in order to determine the extent of the achievement that could be reached by improving output and efficiency of maize with a particular technology. This study assessed technical efficiency of the farms by means of slacks-based measure (SBM) of efficiency model. Tone (2001) proposed a non-radial DEA model called SBM to analyzed input and output slacks directly. The SBM model gives efficiency scores of between zero and one and becomes one if only the decision making unit (DMU) under investigation is on the frontiers of the production possibility set with no input and output slacks. This differentiates it from the traditional DEA model that does not take account of the presence of slacks which leads to bias estimates of efficiency (Fukuyama and Weber, 2009).

Empirical studies that assessed the production efficiency of food crops are many, but those that concentrated on maize are very few in Nigeria. For example, Oyewo *et al.* (2009) analyzed the causes of technical efficiency in maize production in Nigeria, and reported that the farmers achieved an average technical efficiency of about 0.84, which means that farmers were justly efficient in the use of inputs. Ibrahim *et al.* (2014) analyzed the technical efficiency in maize production and its causes across the agro-ecological zones of northern Nigeria. They stated that the average technical efficiency of southern guinea savannah, northern guinea savannah, and Sudan savannah were 86.7%, 83.4%, and 83.8%, respectively. Equally, Ayinde *et al.* (2015) observes the technical efficiency of maize production in Ogun State, Nigeria and



reported an average technical efficiency of 69% which shows that output can be improved by 31% with the existing technology. Simonyan *et al.* (2011) studied the relative technical efficiency and its determinants on gender basis in maize production in Akwa Ibom State, Nigeria. The findings reveal that an average technical efficiency of both male and female farmers was 93% and 98%, respectively.

Based on the encountered empirical literatures, the paper is the first effort to study the efficiency of maize producing farms in Nigeria by comparing TE scores of DEA and SBM models, inputs slacks, super-efficiency scores and super-slacks associated with the maize farms. Besides, the study investigated the determinants of inefficiency if there was any in the farming practices.

With reference to efficiency measurements, the frontier estimation approach was proposed by Farrell (1957), but in-depth empirical application was not given to the approach until a paper by Charnes *et al.* (1978) in which the term Data Envelopment Analysis (DEA) was first used. Ever since, a large number of papers have applied and extended the methodology in the fields of agriculture, banking, education, manufacturing, transportation and health (Liu *et al.*, 2013; and Iliyasu *et al.*, 2016). The wide application of DEA is an indication of its strength and ability in determining firms' technical efficiency. DEA is a mathematical programming approach which constructs production frontiers and measures efficiency relative to the constructed frontiers. The frontier in DEA is a piecewise linear combination that assigns the set of best-practice firms in the data set under analysis thereby yielding a convex Production Possibility Set (PPS). The efficiency estimate for a particular DMU is not defined by an absolute standard but relative to other DMUs in the data set under consideration.

The existence of the inherent dependency among the efficiency scores violates one of the basic assumptions of regression analysis (independence within the sample) which undermine the conventional method thereby making the efficiency estimates inappropriate (Casu and Molyneux, 2003). The radial DEA model does not provide information regarding the efficiency of the specific inputs or outputs used in the production course (Zhou *et al.*, 2012). Besides, radial efficiency measures neglect slack variables, leading to biased estimations (Fukuyama and Weber, 2009) and has a weak discriminating power for ranking and comparing DMUs (Zhou *et al.*, 2007). Due to these limitations, recent studies developed non-radial DEA approaches (Fukuyama and Weber, 2009; and Zhou *et al.*, 2012). Among non-radial efficiency approaches, Tone (2001) developed a Slacks-Based Measure (SBM) of efficiency model which deals directly with input excesses and output shortfalls of each observation called slack variables. According to Tone (2001), SBM model has the advantage of capturing the whole aspect of inefficiency. This property is particularly suitable for analyzing excess inputs reduction such as that use in maize production.

Despite this improvement, the use of SBM method has been limited in determining the efficiency of maize production. Certainly, Ahmed *et al.* (2016) work is the only study to have used this method to estimate technical efficiency in maize production. Most other studies applied the conventional radial DEA model and parametric model (SFA) to estimate the technical efficiency of maize production. Therefore, this inspires the use of both SBM and DEA



methods to estimate and compare the technical efficiency (TE) scores and inputs slacks associated with the variables in the study.

MATERIALS AND METHODS

The Study Area

The study was carried out in north eastern Nigeria which comprise of Adamawa, Bauchi, Borno, Gombe, Taraba and Yobe states with an estimated population of 25 million people. The rainfall duration in this region lies between three to six months a year with about 800mm and 1,500mm per annum. The driest months are February and March, while the wettest months are August and September with a relative humidity of 37% (NiMet, 2018). Agricultural crops produce in the study area include: maize, millet, sorghum, rice, wheat, guinea corn, soybeans, cassava, cowpea and groundnut. In addition to crop farming, some farmers keep livestock such as cattle, sheep, goats and poultry (Sajo and Kadams, 1999).

Sampling Techniques

Smallholder maize farmers in Nigeria were the target respondents for this study. A questionnaire was designed and used to gather data from the farmers face to face in their farming communities. The questionnaire contains data on production activities and the socio-demographic features of the farmers such as gender, marital status, and household size, and local government area (LGA), State of origin, age and education. Data in respect to their production inputs usage and the outputs produced for a single cropping season were collected. Multi-stage sampling technique was used. The first stage consists of the selection of two (2) States (Gombe and Taraba) based on their eminence in maize production activities in the region. The second stage consists of the selection of two (2) Local Government Areas (LGAs) in each State summing to a total of four (4) LGAs. In the third stage, the lists of maize farmers were acquired from the respective State agricultural development programmes of the selected LGAs; and in each case, a simple random sampling technique was used to select farmers from each LGA. Finally, a total of 300 questionnaires were administered to the selected maize farmers, but then only 291 respondents was used for the analysis due to incomplete responses by some farmers.

Method of Data analysis

Data gathered from the farmers were exposed to inferential statistics such as slacks-based measure of efficiency analysis, data envelopment analysis, slacks based super-efficiency model, and ordinary least squares (OLS) analysis. The SBM and DEA models were employed to estimate and compare the efficiency levels of maize farms and input slacks (input excesses) of each variable. Slacks based super efficiency model was used to estimate the super-efficient farms (i.e. farms having efficiency scores above one) and the super-slacks. OLS model was employed to analyze the determinants of technical inefficiency in the study area. The variables under consideration in this study include one output and four production inputs such as maize output/hectare measured in kilogram (kg), fertilizer used/hectare (kg), quantity of seeds/hectare (kg), labour (man-days)/hectare and agrochemicals used (liters)/hectare. However, the variables were measured using DEAfrontier and DEAP version 2.1.



Analytical Techniques

The input-oriented variable returns to scale (VRS) approach in both SBM and DEA models were employed to estimate the TE of farm levels using the same set of inputs in order to provide the basis for comparison between the two (2) models. The choice of VRS model stemmed from the fact that maize farmers have more control over production inputs than output in this study.

Following Tone (2001), the slacks-based measure of efficiency model is specified as:

$$P_i = \min 1 - \frac{1}{n} \sum_{i=1}^n \frac{s_i^-}{x_{i0}} \quad \dots(1)$$

Subject to: $x_0 = X\lambda + s_i^-$, ($i = 1 \dots n$),

$$y_0 = Y\lambda - s_r^+ \quad (r = 1 \dots s),$$

$$\lambda \geq 0, S^- \geq 0, S^+ \geq 0.$$

where;

P = efficiency index.

x_{i0} = quantity of input i used by the maize farm under consideration.

S^- = inputs slacks variables.

S^+ = output variable slacks.

$i = 1, 2 \dots n$ index of inputs.

n = number of inputs (fertilizer, seeds, man-days of labour and agrochemicals).

$r = 1, 2 \dots y$ index of maize outputs.

Subscript "O" is the maize farm whose efficiency has been evaluated in the model.

λ = non-negative multiplier vector used for calculating a linear combination of variables.

The resulting condition will hold if a farm is technically efficient; $P^* = 1$, $\lambda^* = 0$, $S^{-*} = 0$ and $S^{+*} = 0$. This signifies an optimal solution, that is, no input excesses and no output deficits (Tone, 2001).

Following (Banker *et al.*, 1984; and Casu and Molyneux, 2003), the VRS input-oriented DEA model for estimating the TE of maize farms is specified as:

$$\text{Min}_{q,l} q, \quad \dots(2)$$

Subject to;

$$-y_i + Yl \geq 0$$

$$qx_i - Xl \geq 0$$

$$N1'l = 1$$

$$l \geq 0$$



The subscript i represents the i^{th} maize farm, q is the TE score which ranges from 0 to 1, l is an $N \times 1$ vector of ones that defines the linear combination of the peers of the i^{th} farm, Y is a vector of maize output quantities (kg/ha) and X is a vector of observed inputs (fertilizer, seeds, labour and agrochemicals). The term $-y_i$ is the vector of output of the i^{th} maize farm compared with the output vector of the theoretically efficient maize farm (Yl).

The slacks based super-efficiency model is used to estimate and identify super-efficient maize farms and the super-slacks as proposed by Tone (2002):

$$\pi_I^* = \min \frac{1}{n} \sum_{i=1}^n \frac{\bar{x}_i}{x_{io}} \quad \dots(3)$$

$$\text{Subject to: } \bar{x}_i \geq \sum_{i=1, i \neq 1}^n x_i l_i \quad (i = 1 \dots n),$$

$$\bar{y}_r \leq \sum_{i=1, i \neq 1}^n y_r l_i \quad (r = 1 \dots s),$$

$$\bar{x}_i \geq x_o, \bar{y} \leq y_o, l \geq 0.$$

where;

The index (π^*) = product of the distance in the input space and the distance in the output space.

The numerator expresses an average reduction rate of $\bar{x}_i$ to x_i .

To estimate the technical inefficiency analysis, and following Banker and Natarajan (2008), the OLS model is specified as follows:

$$Q_i = \gamma_0 + \gamma_1 W_1 + \gamma_2 W_2 + \gamma_3 W_3 + \dots + \gamma_6 W_6 + \varepsilon_i \quad \dots(4)$$

where;

Q = technical inefficiency scores.

W_1 = farmers' age (years).

W_2 = experience (number of years spent in maize farming).

W_3 = education (years spent in school).

W_4 = non-farm work (dummy: 1 = if a farmer engaged in non-farm work, 0 = otherwise).

W_5 = extension contact (dummy: 1 = if a farmer had contact with an extension agent, 0 = otherwise).

W_6 = household size of farmers (number of people per household).

$\gamma_o - \gamma_6$ = vector of coefficients.

ε_i = error term.



RESULTS AND DISCUSSION

Technical efficiency Results of DEA and SBM Models

The study estimated the technical efficiency results of maize farmers' using DEA and SBM models (Table 1). The efficiency estimates of DEA model ranges from 0.51-1.00, while that of SBM model ranges from 0.41-1.00. The results indicate that the average technical efficiency of both DEA and SBM models were 0.78 and 0.66, respectively, which implies that maize farms in the sample were operating below the frontier technology. However, the computed results from both models signify that maize farms could increase their respective technical efficiency levels by about 22%% and 34% with the available levels of input and technology. The results agrees with the findings by (Umoh, 2006; Oluwatayo *et al.*, 2008; and Ahmed *et al.*, 2016) who reported similar technical efficiency estimates. The variation in the efficiency scores between the two models (DEA and SBM) is due to the fact that SBM efficiency model is non-radial and deals with the specific inputs/output of each farm directly thereby capturing the whole aspect of inefficiency and hence, gives more reliable efficiency estimates (Tone, 2001) whereas DEA is non-radial measure of efficiency based on the proportional reduction of input/output which does not provide information about the efficiency of the specific input or output used in the production which leads to bias estimation of efficiency (Fukuyama and Weber, 2009; and Zhou *et al.*, 2012).

Table 1: Technical Efficiency Scores of SBM and DEA Models

TE Range (SBM Model)	Frequency	Percentage	TE Range (DEA Model)	Frequency	Percentage
0.31 ≤ 0.40	7	3.7	-	-	-
0.41 ≤ 0.50	30	16.2	0.41 ≤ 0.50	-	-
0.51 ≤ 0.60	57	30.8	0.51 ≤ 0.60	16	8.6
0.61 ≤ 0.70	41	22.2	0.61 ≤ 0.70	32	17.3
0.71 ≤ 0.80	19	10.3	0.71 ≤ 0.80	51	27.6
0.81 ≤ 0.90	9	4.9	0.81 ≤ 0.90	35	18.9
0.91 ≤ 0.99	2	1.1	0.91 ≤ 0.99	18	9.7
Efficient farms	20	10.8	Efficient farms	33	17.8
Total	291	100.0	Total	291	100.0
Mean	0.66	-	Mean	0.78	-

Source: Field work (2020)

Comparative Analysis of DEA and SBM Input Slacks

The inputs slacks analysis was conducted to identify the farms that used excess inputs which lead to inefficiency and to compare the levels of slacks obtained using DEA and SBM efficiency models (Table 2). The results indicate the presence of inputs slacks, implying that farm inputs were over-utilized during the production process. The DEA analysis shows that farmers over-utilized labour in excess of 4.71, agrochemicals by 1.78, fertilizer (23.83) and seeds by 4.29 whereas the SBM analysis reveals that farmers over-utilized labour by 2.44, agrochemicals in excess of 0.66, fertilizer input by 15.37 and seed was over-utilized by 2.23.



Also, in Table 2, the DEA and SBM slacks analysis shows that farmers' loss the amount of profit which could have accrued to them by about \$43.16 and \$22.52, respectively, due to inappropriate use of inputs (excess inputs used). The DEA analysis implies that maize farmers could operate on the production frontier by reducing their labour input by 4.71%, agrochemicals by 1.78%, fertilizer by 23.83% and seeds by 4.29%; whereas the SBM analysis implies that labour input could be reduce by 2.44%, agrochemicals by 0.66%, fertilizer by 15.37% and seeds by 2.23%. The excess inputs usage could be attributed to the fact that the sampled maize farms operate at a subsistence level and lacks the knowledge of proper amount of inputs to use on their farms. They typically depend on their farming experience which leads to inefficient use of the farm inputs. However, the consequence of inputs over-utilization leads to increase in production costs and low profit for the farmers. According to Cooper *et al.* (2000), technically inefficient farms could be efficient and reach the production frontier through input slacks adjustment.

The difference that exists between DEA input slacks and SBM input slacks is an indication of biasedness that occurs in the radial DEA model. This is because the radial DEA adjusts all undesirable outputs and inputs by the same proportion to efficient targets (Charnes *et al.*, 1987). The radial efficiency measures neglect slack variables and have a weak discriminating power for ranking and comparing DMUs whereas non-radial efficiency measures (SBM) deals with input and output slacks directly and has the advantage of capturing the whole aspect of inefficiency (Zhou *et al.*, 2007; Fukuyama and Weber, 2009; and Zhou *et al.*, 2012). Thus, SBM gives more accurate, reliable and unbiased efficiency and slacks estimates than the DEA model.

Table 2: Inputs Slacks obtained from DEA and SBM Analysis per Hectare

Inputs	DEA Slacks	Value (\$)	SBM Slacks	Value (\$)
Labour	4.71	13.24	2.44	6.86
Agrochemicals	1.78	10.91	0.66	4.05
Fertilizer	23.83	13.82	15.37	8.91
Seeds	4.29	5.19	2.23	2.70
Total	34.61	43.16	20.70	22.52

Source: Field work (2020)

T-test Analysis

The T-test analysis was used to compare the mean difference between input slacks and the technical efficiency estimates of DEA model and SBM model (Table 3). The results indicate that labour, agrochemicals and seeds slacks were statistically significant at varying levels of probability. In regards to efficiency analysis, the results also indicate that there is a statistically significant difference between the TE estimates of DEA model and SBM model at 1% level of probability ($P \leq 0.01$). This implies that DEA model have higher efficiency



estimates in terms of inputs slacks and technical efficiency scores than SBM model. The higher inputs slacks and TE estimates were due to the bias nature of the DEA model which does not provide information regarding the efficiency of the specific inputs or outputs used in the production course (Zhou *et al.*, 2012).

Table 3: T-test Results of SBM and DEA Inputs Slacks

Variable inputs	Slacks mean difference	T-value	P-value	95% confidence interval of the difference	
				Lower	Upper
Labour	2.28	1.92	0.056**	-0.06	4.61
Agrochemicals	1.12	4.69	0.000*	0.65	1.59
Fertilizer	8.46	1.40	0.162 ^{NS}	-3.42	20.34
Seeds	2.06	3.20	0.001*	0.79	3.32
Efficiency scores	0.12	9.36	0.000*	0.13	0.19

Source: Field work (2020)

Analysis of Super-Efficiency Scores and Super-Slacks Variables

The data envelopment analysis (DEA) established by Charnes *et al.* (1978) and Cooper *et al.* (2000) has shown that the best DMUs gives an efficient score denoted by unity (1.00). To distinguish between these efficient DMUs in DEA dimension, the slacks-based super-efficiency analysis is required. The analysis was conducted to detect the super-efficient farms that scored values above 1.00. The results indicate that the farmers were super-efficient because of their ability to save labour input by 2.08%, agrochemicals by 0.71%, fertilizer by 2.32% and seeds input by about 1.04% (Table 4). The super-slacks were multiplied by the unit prices of each variable input used per hectare as shown in Table 4 and the solution provides a total of \$5.72, which reflects the amount of profits gained from the inputs as a result of super-efficiency. The findings also reveal that in spite of the inefficiencies in the farming practices, 15 farms were super-efficient. These super-efficient farms are regarded as the best farms that are exceptionally efficient and have the potential inputs savings as stated by (Chen, 2005 and Zhou *et al.*, 2012).

Table 4: Analysis of Super-Efficiency Scores and Super-Slacks of the Farms

SE scores range	Frequency	Percentage	Variables	Super-slacks	Value (\$)
1.0 – 2.0	6	47.40	Labour	2.08	1.21
2.1 – 3.0	3	23.70	Seeds	1.04	0.40
3.1 – 4.0	4	10.50	Fertilizer	2.32	3.25
4.1 – 5.0	2	18.40	Agrochemicals	0.71	0.86
Total	15	100.0	-	6.15	5.72

Source: Field work (2020)



Determinants of Technical Inefficiency

Ordinary least square model was employed to evaluate the determinants of technical inefficiency of the farms in the study area. To observe some of these variations, technical efficiency estimates of the farms were regressed on some certain variables such as education, non-farm work, experience, age, extension and household size. Table 5 shows the findings of the OLS model. The findings from the model point out that all estimated variables consist of the expected signs. Age variable is statistically significant at 5% level of probability. This implies that age increases technical inefficiency. The reason could be based on the fact that most of the activities conducted in maize farming are vigorous and therefore as the farmers grow older, they become less active in undertaking such operations. Similarly, Bozoğlu and Ceyhan (2007), Paudel and Matsuoka (2009) reported that age increases technical inefficiency among farmers.

The household size variable is not statistically significant but has a negative sign which is desirable. This signifies that households with more number of inhabitants tend to offer more labour for farm works which in turn increases technical efficiency than those with less number of people. The result agrees with the findings of Feng, (2008), who stated that families with more number of dependents in Jiangxi Province (China) were technically more efficient in production. Educational level of farmers was statistically significant and has the correct sign. This denotes that educational level of farmers' decreases technical inefficiency across farms and that farmers with more years of education are likely to move closer to the frontier technology. This result is consistent with the findings from similar studies as conducted by (Ojo & Ogundari, 2006; and Bozoğlu and Ceyhan, 2007; and Alene *et al.*, 2008). Therefore, education is important in acquiring farming skills and adoption of new innovations which could improve efficiency in the study area.

The coefficients of experience have the expected sign and significantly reduced technical inefficiency. This means that respondents with many years of farming experience are expected to be more efficient because of the long involvement in maize production. This result supports the findings of Ojo and Ajibefun (2000) and Abu *et al.* (2012) who indicated that an increase in the number of years in farming reduces technical inefficiency. The coefficient of extension services in the model has a negative sign and is statistically significant. This implies that maize farmers who were offered extension services are more efficient since they can certainly acquire new skills and enhanced technology.



Table 5: Determinants of Technical Inefficiency in Maize Farming

Variables	Coefficient	Standard error	T-value	P-value
Constant	0.1324617	0.4245557	0.31	0.757 ^{NS}
Education	-0.3517168	0.1208231	-2.91	0.004*
Experience	-0.0034965	0.0012635	-2.77	0.006*
Non-farm work	0.1867395	0.1296574	1.44	0.150 ^{NS}
Age	0.0174138	0.0089855	-1.94	0.053**
Household size	-0.0026012	0.0169521	-0.15	0.878 ^{NS}
Extension services	-0.0040599	0.0014274	-2.84	0.005*

Note: * and ** are 0.01% and 0.10% levels of significance; and NS is insignificant variables

Source: Field work (2020)

CONCLUSION AND RECOMMENDATIONS

The study estimated and compared the technical efficiency of maize producing farms in Nigeria using DEA and SBM models. The findings indicate that the average TE scores of DEA (0.78) are higher than that of SBM analysis (0.66). Generally, results from both DEA and SBM models show that only 17.8% and 10.8% of the maize farmers are technically efficient whereas 82.2% and 89.2%, respectively, are operating below the production frontier technology. The slacks analysis indicates that DEA has higher inputs slacks (34.61%) than the SBM model (20.70%), implying inputs over-utilization during the production period. The variation in the TE scores and slacks estimates is due to the fact that DEA model adjusts all inputs and output by the same proportion to efficient targets and neglect slacks variables leading to bias estimates whereas SBM technique measures efficiency based on the information of specific inputs or outputs used in the course of production and takes account of the existence of slacks which consequently gives accurate and reliable estimates. The finding showed that regardless of the inefficiencies in the farming practices, some farms turn out to be super-efficient and are regarded as the best leading farms capable of saving inputs. The technical inefficiency analysis indicates that all estimated variables have the expected signs and that education, household size, experience and extension services reduced technical inefficiency, while age and non-farm work increases technical efficiency in the study area.

Therefore, super-efficient farms should be used as a bench-mark by the inefficient farms thereby applying the recommended quantity of inputs desired for production. This can reduce inefficiencies and lead to more output and reduced production costs incurred by farmers. This study focused on DEA and SBM models to estimate TE scores, hence prospective studies should endeavor to study other models such as stochastic frontier analysis (SFA) and parametric distance function (PDF) in order to compare the TE scores with that of SBM model. The main contribution of the study is in comparing the efficiency of maize producing farms through the application of both radial and non-radial measures of efficiency approach (i.e., DEA and SBM techniques). Moreover, the study was the first on maize production to explore both super-efficiency scores and super-slacks concurrently.



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