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Impact of Microfinance on the Efficiency of Maize Producers in Nigeria

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Abstract: The study applies descriptive analysis, Slacks-Based Measure (SBM) of efficiency model and fractional regression model to data collected in 2016 using cross-sectional survey of maize producers in Nigeria. The purpose was to determine the impact of microfinance on the technical efficiency of maize producers and evaluates factors that influence inefficiency among credit beneficiaries and non-credit beneficiaries. Results show that the respective mean technical efficiency of credit beneficiaries and non-credit beneficiaries were 79 and 69%, which is far from the frontier technology. This means that technical efficiency can be improve by 21 and 31% respectively, with the same set of inputs. Slacks analysis shows that in order to attain optimum efficiency, credit beneficiaries should reduce fertilizer usage by 32.34%, seeds by 6.03%, labour by 7.79% and agrochemicals by 2.44% per hectare. Similarly, non-credit beneficiaries should reduce the usage of fertilizer slacks by about 19.48%, seeds by 2.73%, labour by 2.54% and agrochemicals slacks by 1.76% per hectare. Microfinance credit, household size, years of farming experience and education increases efficiency, while drought and age declines efficiency. Findings are useful to the farmers as appropriate input reduction for inefficient farms can be set to enable them attain optimum efficiency level. Maize producers should be encouraged to collect microfinance loan in order to increase their scale of operations and government in collaboration with research institutes should educate farmers on the actual input quantities to apply. This could help to reduce production costs, increase the farmers' efficiency and provide maize to consumers at an affordable rate.

Keywords: Credit Beneficiaries, Fractional Regression Model, Maize Producers, Non-Credit Beneficiaries, Slacks-Based Measure Model, Technical Efficiency

Introduction

Maize (Zea mays L.) is cultivated extensively all over the world in a series of agro-ecological environments occupying over 160 million hectares. The reported worldwide maize production reached approximately 1.022 billion tons in 2014, which recorded a slight increase by 0.09% as compared to the year 2013. America produced about 52% of the total world maize production in the year 2014. This is followed by Asia (29.76%), Europe (11.03%), Africa (7.57%) and others (0.13%) respectively (FAOSTAT, 2015). Maize has turn out to be one of the Africa's leading food crops where East Africa happens to be the largest producer (32 million tons) which accounted for about 41% of the total maize produced in the year 2014, followed by West Africa (20 million tons) which is equivalent to 25.15%. Other regions that play a vital role in maize production comprises of South Africa (19.64%), North Africa (7.70%) and Central Africa being the least producer with only 7%. According to FAOSTAT (2016), Nigeria is the leading maize producer in West Africa with about 7.2 million tons in 2016 (Table 1).

Nigeria has a potential for maize production which accounts for about 55.26% of all the maize grown in West and Central Africa. In the year 2014 for instance, about 5.9 million hectares of land were cultivated for maize production (FAOSTAT, 2015). Despite its importance and various efforts made by government and Non-Governmental Organization (NGO) through the introduction of new varieties of seeds, seedlings and zero tariffs on imported agrochemicals, average per hectare maize yield in Nigeria was about 2.0 metric tons which is lower than the global average of 5.1 metric tons per hectare (Ibrahim *et al*., 2014). Thus, maize production does not meet the local demand which leads to the importation of about 0.81 million tons of maize amounted to USD1.1 Million in 2014 (FAOSTAT, 2015).

This low level of maize production could be attributed to technical inefficiency at the farm level. However, maize farmers may be facing different challenges in managing their farms and these may contribute either directly or indirectly to technical inefficiency. Factors such as farming experience, age of the farmers, frequency of contact with extension personnel, prevalence of drought, educational level, non-farm activities, household size, farm size, access to credit facilities and adaptation of new innovations may be responsible for the technical inefficiency at the farm level. Thus, it is against this background that the present study determines the impact of microfinance on the efficiency of maize producers and evaluates factors that influence inefficiency in the North-Eastern Nigeria in order to formulate policy that will assist in improving this important sector.

Methods of Efficiency Measurement

The common methods of estimating efficiency have been based on two frontier models: Namely parametric (SFA) and non-parametric (DEA). The parametric models are mainly measured based on econometric methods whereas the non-parametric models used linear programming method to construct a non-parametric 'piece-wise' surface (or frontier) over the data (Coelli *et al*., 1998). Farrell (1957) proposed the use of either a non-parametric piece-wise linear convex isoquant made in such a way that no observed points should lie to the left or below it, or a parametric function such as Cobb-Douglas production function.

DEA technique is widely used to measure the comparative efficiency of a firm by providing an estimate for the analysis of inefficient firms onto an efficiency frontier (Charnes *et al*., 1978). DEA can be applied using either an output based (output expansion) or an input-based (input reduction) or both, depending on whether these approaches use input distance function or output distance function. From input-oriented approach, the efficiency of these firms are calculated as the amount of inputs that could be reduce relative to the inputs levels of the best performing firms in order to produce the same level of output. While the output oriented approach calculates the amount of output that could be increase with the same level of input.

Table 1. Maize production in Nigeria from 2010-2016 (tons)

Year	Production (1,000 MT)	Percent
2010	8,800	15.97
2011	9,250	16.79
2012	7,630	13.85
2013	7,700	13.98
2014	7,515	13.64
2015	7,000	12.71
2016	7,200	13.07
Total	55,095	100

Source: (FAOSTAT, 2016)

There have been many theoretical developments in practical applications of DEA since its invention by Charnes *et al*. (1978), especially in the fields of agriculture, banking, education, health, manufacturing and transportation. The method has numerous advantages as indicated by Ray (2004; Coelli *et al*., 1997; Heady and Kohli, 2010). It is a non-parametric technique that does not need a prior specification of the functional form for the production frontier (Coelli *et al*., 1998). DEA can handle multiple inputs and outputs automatically without being combined. It makes possible the identification of the best practice for every decision-making unit under study and estimate the output or cost gap of inefficient firms to be fully efficient. The radial DEA suffers from major limitations which includes it sensitivity to extreme observations and attributes all deviations from the frontier to inefficiency, the piece-wise linear convex isoquant assumes that no observed point lies to the left or below it and large problems can be computationally severe due to the creation of a separate linear program for each decision making unit. It does not take account of the existence of slacks because it is based on the proportional reduction of inputs or output expansion that makes it impossible to capture the whole aspect of inefficiency leading to bias estimates (Tone, 2001; Zhou *et al*., 2007; Fukuyama and Weber, 2009; Ramalho *et al*., 2010; Zhou *et al*., 2012).

The limitations in radial (traditional) DEA model motivates Tone (2001) to proposed Slacks-Based Measure (SBM) of efficiency model (non-radial) which captures slacks variables directly and is considered to be more accurate in estimating efficiency scores than the conventional DEA as used by Ramalho *et al*. (2010) and Zhou *et al*. (2012). Despite this development, the application of SBM model has thus far been limited in measuring the efficiency of maize production. In fact, no study to our knowledge has used this technique to estimate efficiency in maize production.

Most other studies have employed the conventional DEA and SFA models to estimate technical efficiency of maize. For instance, Ajao *et al*. (2005) examines the comparative efficiency of mechanized and non-mechanized maize farms in Oyo State, Nigeria using SFA approach and revealed that the mean technical efficiency of mechanized farms was 0.72 whereas non-mechanized farms had 0.62. Alene and Hassan (2006) compared the efficiency of traditional and hybrid maize production in eastern Ethiopia using DEA. These findings show that farmers are technically inefficient and as such they were able to attain a mean technical efficiency levels of 0.68 and 0.78, while Olarinde (2011) analyzed technical efficiency differentials and their determinants among maize farmers in Nigeria using SFA. The results indicate that the sampled farms had respective mean technical efficiencies of only 0.56 and 0.58 in Oyo and Kebbi states.

Similarly, Dangwa (2011) compares technical efficiency of maize between A1 resettlement areas and communal areas in Mashonaland East Province of Zimbabwe using SFA and his findings show that communal farmers has higher technical efficiency (0.81) scores than their A1 (0.64) counterparts, while Ansah (2014) investigates the profit efficiency of maize and cowpea production in Ashanti Region of Ghana using SFA and postulates that the mean profit efficiency of maize farmers was 0.89, while cowpea recorded up to 0.95 level of efficiency. Kidane and Ngeh (2015) analyzed technical efficiency of smallholder maize farmers in Tanzania via the use of SFA and discovered that farmers attained an efficiency level of only 0.74. However, the findings of the above studies indicate that a considerable level of inefficiency exists and that farmers could improve their efficiency levels if resources are properly harnessed and utilized. Moreover, there is no doubt that none of the preceding studies operated at the frontier technology. Thus, this study employed Slacks-Based Measure (SBM) of efficiency model to estimate technical efficiency of CB and NCB farms.

Methodology

This section introduces the sampling method, data collection method and the models engaged in data analysis.

Sampling Technique

Four states (Adamawa, Bauchi, Gombe and Taraba) of the six states in North-Eastern Nigeria were purposively selected for this study based on the concentration of maize farmers and the presence of microfinance activities. Two Local Government Areas (LGAs) were further selected from each state based on the prominence of maize production and microfinance activities. Furthermore, the farmers were group in to two based on Credit Beneficiaries (CB) and Non-Credit Beneficiaries (NCB) in order to obtain a homogeneous distribution of the population. Finally, simple random sampling technique was used to select the CB respondents from the lists provided by microfinance banks located in each of the selected LGA whereas NCB respondents were selected from the list provided by the respective states' agricultural development projects of the selected LGAs of the states.

Data Collection

Data for this study were collected using a structured questionnaire administered to the selected maize farmers. Information on the inputs used during 2016 production season and the outputs produced was collected. A total of 600 questionnaires were finally administered to the selected maize farmers, but only 525 questionnaires were correctly filled and retrieved from the respondents. The valid responses comprised of 269 CB maize farms and 258 NCB maize farms. The required sample size from both groups was obtained using the method established by Yamane (1967).

Thus, the formula is given by:

$$n = \frac{\mathrm{N}}{1 + \mathrm{N}\left(e^2\right)} \tag{1}$$

Where:
N = Sample frame of the population
e = Sampling error at 5% (0.05)
n = Sample size

Analytical Techniques

Descriptive analysis, Slacks-Based Measure (SBM) of efficiency and fractional regression models were employed. SBM technique was employed to estimate the technical efficiency scores as well as input slacks (Tone, 2001). SBM provides information regarding the efficiency of the specific input used by a particular farm or output obtained and deals with input and output slacks directly thereby capturing the whole aspect of in efficiency. The model returns an efficiency scores of between 0 and 1 and gives unity if and only if the farm concerned is on the frontiers of the production possibility set with no input/output slacks. The model has three variations, i.e., input-oriented, output-oriented and non-oriented. The non-oriented model indicates both input-oriented and output-oriented models and can be applied if both inputs and outputs efficiencies are to be evaluated concurrently. Even though many of the preceding studies used Tobit regression model (Alam, 2011; Sihlongonyane *et al*., 2014; Ibrahim *et al*., 2014) and Ordinary Least Squares (McDonald, 2009; Iliyasu and Mohamed, 2015; Iliyasu *et al*., 2016) in the second stage analysis, Papke and Wooldridge (1996) argued that the use of such models are inappropriate in this situation. Data defined on the interval [0, 1] such as DEA scores requires the use of regression models that are appropriate in dealing with fractional data in the second stage DEA analysis. however, the DEA results in this study reveals that all farms have scores above zero and since the second stage DEA analysis is been carried out to estimate the determinants of technical inefficiency, this implies that all farms that are operating at one are already efficient so there is no need to conduct further analysis. As a result, the remaining observations become fractions and hence the need for fractional regression model to estimate the determinants of technical inefficiency as suggested by (Papke and Wooldridge, 1996; Hoff, 2007; Ramalho *et al*., 2010).

Model Specification

Slacks-Based Measure (SBM) of Efficiency Model

The SBM input-oriented model was adopted for the study to estimate technical efficiency and input slacks because maize farmers have control over their farm inputs than they do over output. The model is expressed as follows:

$$\rho_I = \min\ 1 - \frac{1}{m}\sum_{i=1}^{m} \frac{s_i^-}{x_{i0}} \tag{2}$$

$$\begin{aligned} &Subject\, to: x_0 = X\lambda + s_i^-, (\mathrm{i} = 1...\mathrm{m}) \\ &y_0 = Y\lambda - s_r^+, (\mathrm{r} = 1 ...\mathrm{s}) \\ &\lambda \geq 0, S^- \geq 0, S^+ \geq 0 \end{aligned}$$

Where:

x_{io}	=	The amount of input i used by a particular farm
y_0	=	The amount of output produced by a Particular farm
s^-	=	Input slack variables
s^+	=	Output slack variables
m	=	Number of inputs used during production
r	=	Number of output
ρ_I	=	SBM-input-efficiency
Sub-index$_I$	=	Cross-sectional data
Subscript "*O*"	=	The farm whose efficiency is being estimated in the model
λ	=	Non-negative multiplier vector used for computing a linear combination of variables

The following condition will hold if a farm is efficient; $\rho_I^* = 1$, $= \lambda^* = 0 s^{-*} = 0$ and $s^{+*} = 0$ (Tone, 2001).

Fractional Regression Model

Following (Papke and Wooldridge, 1996; Hoff, 2007; Ramalho *et al*., 2010), fractional regression model was adopted to estimate the determinants of technical inefficiency in which the dependent variable contained fractional data (i.e., the technical inefficiency scores). The model was estimated by Quasi-Maximum Likelihood technique (QML) using STATA 14 and is explicitly specified as:

$$\begin{aligned} Y_i &= \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \\ &\beta_3 X_3 + \beta_4 X_4 + \ldots + \beta_8 X_8 + \varepsilon_i \end{aligned} \tag{3}$$

Where:

Y_i	=	Represents the technical inefficiency scores which are in form of fractions i.e., the efficiency scores are greater than zero and less than one [$0 < Y < 1$].
X_1	=	Off-farm activities
X_2	=	Ducation
X_3	=	Drought
X_4	=	Household size
X_5	=	Age
X_6	=	Experience
X_7	=	Extension contact
X_8	=	Microfinance credit
β_1-β_8	=	Vector of coefficients
ε_i	=	Error term

Variables Definition

In this study, five variables were used to measure technical efficiency and slacks variables as presented in Table 2. These include one output and four inputs. The output represents maize yield produced by each farmer during the production season weighted in kilogram per hectare. Inputs include labour, fertilizers, seeds and agrochemicals used. Labour signifies the per hectare human labor engaged during the entire production period including children, adult men and women. Fertilizer input along with other technologies plays an important role in maize production and has the potential to boost crop productivity. However, inorganic fertilizer was used in this study and was measured in kg/ha. The quantity of seeds involved in maize production was measured in kg/ha. According to Fekadu and Bezabih (2009), seeding rate is a factor which determines production level. Agrochemical is defined as the amount of chemicals such as herbicides, insecticides and pesticides applied to the sampled maize farms in order to avert the adverse effect of weed, insects and pests during the production period so as to increase productivity in the study area. Table 2 also shows the variables used to examine the determinants of technical inefficiency in maize production.

Table 2. Description of variables in SBM and fractional regression models

Variables in the models	Description	Unit
Dependent variable		
Output	Maize output/ha	Kilogram
Independent variables		
Fertilizer	Quantity of fertilizer used/ha	Kilogram
Seeds	Quantity of seeds used/ha	Kilogram
Labour	Total hours of family and hired labour spent working on the farm/ha	Man-days
Agrochemicals	Quantity of chemicals applied/ha	Liters
Determinants of inefficiency		
Dependent variable		
Inefficiency estimates	One min technical efficiency scores	
Independent variables		
Off-farm activities (X_1)	Activities engaged outside farm operations	Dummy
Education (X_2)	Years spent in school	Dummy
Drought (X_3)	Prolonged cessation of rainfall	Dummy
Household size (X_4)	Number of people per household	Continuous
Age (X_5)	Represents age of maize farmer	Continuous
Experience (X_6)	Represents number of years spent in farming	Continuous
Extension contact (X_7)	Visits paid by an extension personnel	Dummy
Microfinance credit (X_8)	Loan collected from microfinance banks	Continuous

Results and Discussion

Estimates of Technical Efficiency Scores

The study estimated input-oriented VRS Model efficiency scores of maize farms using SBM approach. The maize farms were divided into two subsectors based on microfinance CB and NCB in order to develop in-depth analysis of the industry's performance. The estimated mean technical efficiency of CB and NCB were 0.79 and 0.69 respectively (Table 3). Based on these findings, CB farms were the most technically efficient, whereas the NCB farms were the least efficient. The implications drown from this analysis shows that both group of farmers utilized some inputs in an inappropriate proportion which resulted to low efficiency scores as such they still have the potential to increase their corresponding efficiency levels by 21 and 31% with the current level of technology and input levels. The results of this study corroborates with the findings of (Addai and Owusu, 2014; Ansah, 2014; Martey *et al*., 2015) who also reported similar technical efficiency estimates. This provides an opportunity for immediate policy interventions that could aid in countering the inefficiency and push the production frontier technology outward leading to higher efficiency. However, the higher efficiency estimates obtained by CB was as a result of the loan they collected from microfinance banks which facilitated their purchase of more production inputs at the appropriate time and adopts enhanced farming techniques than their NCB counterparts. Besides, existing literatures on the impact of microfinance on maize production indicates that access to credit have improved farmers' productivity as well as their well-being (Adams and Bartholomew, 2010; Ashaolu *et al*., 2011; Nuhu *et al*., 2014).

Slack Variables Analysis

Slack refers to the excess input(s) used in the farm during production process and it is measured as a percentage. The results in Table 4, shows that the estimated percentage of total input slacks of CB and NCB were 48.60 and 26.51% respectively. This implies that both CB and NCB were over utilizing farm inputs such as fertilizer, seeds, labour and agrochemicals and therefore, are technically inefficient. However, the results indicate that CB could operate on the production frontier (optimum efficiency level) by reducing their fertilizer slacks, seeds, labour and agrochemicals levels per hectare by 32.34, 6.03, 7.79 and 2.44% respectively. Similarly, NCB should reduce the usage of fertilizer slacks by about 19.48%, seeds by 2.73%, labour (2.54%) and agrochemicals slacks by 1.76% per hectare. According to Cooper *et al*. (2000), inefficient farmers can become efficient and reach the frontier through slacks adjustment. However, the frequency of slacks was measured by the number of occurrence of each input slacks (excess inputs) in each farm considered in this study.

Technical Inefficiency Analysis

Table 5 shows the determinants of technical inefficiency in maize production. The study used technical inefficiency scores of CB and NCB as the dependent variable for the separate groups and therefore, those variables with a negative sign will have a positive impact on the level of technical efficiency. The findings of both CB and NCB shows that household size, years of farming experience, extension, education and microfinance credit bears negative signs and hence contributes to technical efficiency while, off-farm activities, drought and age contributes to technical inefficiency in maize farming. The pseudo likelihood ratio obtained from both CB and NCB models (-132.37) and (-966.78) respectively, were less than zero which indicates that the model is a good fit. The respective chi-square p-value of CB and NCB were 0.07 and 0.06 which were greater than the selected tolerance level of (0.05). This indicates that the model fits the data adequately.

The coefficient of farmers' experience was found to be negative and statistically significant in the case of CB. This implies that experienced maize farmers are more technically efficient. This is because most farmers have acquired skills over time through learning by doing process and as a result becomes experienced. This finding is supported by Addai and Owusu (2014), who reported that an increase in the number of years in farming increases technical efficiency of maize farmers across various agro ecological zones of Ghana. The coefficient of age variable is positive and statistically significant in both CB and NCB models. This indicates that as the farmers grow older, their technical inefficiency also increases. This may be due to the fact that most of the activities conducted in maize farming are labour intensive. Thus, the more a farmer grows older, the less energetic and less productive they becomes in carrying out such operations. However, the result agrees with the findings of Paudel and Matsuoka (2009) who also, found out that age influenced inefficiency of maize production in Nepal.

Moreover, the coefficient of household size of both CB and NCB has a negative sign and is statistically significant. Maize farmers in most rural areas are poor and thus cannot afford to own modern technology but rather, they mainly depend on manual labour for their farm operations. Therefore, the larger the household size, the more likely they are to be technically efficient in terms of input usage. This result is in conformity with the findings of Oyewo *et al*. (2009) where they studied determinants of maize production in Nigeria and discovered that large family size reduces technical inefficiency in farming practices. In another study by Feng (2008), on technical efficiency of farm household in Jiangxi Province of China also reported that families with large number of dependents were technically more efficient in production.

As expected, the coefficient of drought in respect to both CB (0.846) and NCB (1.293) models were each estimated to be positive and statistically significant. The positive sign is an indication that the longer period of drought increases technical inefficiency in maize production. Inconsistent rainfall distribution during production season is a critical constraint to increased food crop production in the northern part of Nigeria where most of the cereal crops are cultivated (Ismaila *et al*., 2010). The negative coefficient of education variable in both CB and NCB models implies that maize farmers with a higher educational level are likely to be more technically efficient. This result agrees with the findings of Alene *et al*. (2008) and Sihlongonyane *et al*. (2014) who also revealed that maize farmers in Kenya and Swaziland having more years of education tend to be more efficient than their non-educated counterparts.

The result shows that the coefficient of microfinance credit is negative (-0.683) and significant at 1% level of probability. This means that an increase in the amount of credit given to farmers will likely reduce their technical inefficiency by about 0.683. Therefore, microfinance credit have positive impact on the technical efficiency of the borrowers as it empower them to acquire production inputs such as fertilizer, high quality seed, land, herbicides and pesticides at the appropriate time. This results support the findings of Ayaz *et al*. (2011; Sossou *et al*., 2014; Martey *et al*., 2015) who also indicated that credit have positive impact on technical efficiency.

Table 3. Estimated technical efficiency scores of both CB and NCB

ES range (CB)	Frequency	Percent	ES range (NCB)	Frequency	Percent
0.51-0.60	4.00	1.5	0.51-0.60	37.00	14.34
0.61-0.70	57.00	21.2	0.61-0.70	85.00	32.94
0.71-0.80	69.00	25.7	0.71-0.80	55.00	21.32
0.81-0.90	98.00	36.4	0.81-0.90	71.00	27.52
0.91-1.00	41.00	15.2	0.91-1.00	10.00	3.88
Total	269.00	100.0	Total	258.00	100.00
Mean	0.79		Mean	0.69	
Minimum	0.54		Minimum	41.00	
Maximum	1.00		Maximum	1.00	

Source: Computed from field survey, 2015, NB: ES = Efficiency range, CB = Credit Beneficiaries, NCB = Non-Credit Beneficiaries

Table 4. Slacks variables for CB and NCB farms

Inputs	Slacks (CB)	Frequency	Slacks (NCB)	Frequency
Fertilizer	32.34	98	19.48	83
Seeds	6.03	17	2.73	69
Labour	7.79	69	2.54	48
Agrochemicals	2.44	26	1.76	51
Total	48.6	-	26.51	-

Source: Computed from field survey, 2015

Table 5. Fractional regression results of CB and NCB

Variables	CB (n = 269)	Significant	NCB (n = 256)	Significant
Constant	-0.498 (1.124)	0.659 NS	-0.097 (1.492)	0.950 NS
Age	0.131 (0.022)	0.000*	0.182 (0.034)	0.001*
Education	-0.172 (0.037)	0.000*	-1.299 (0.319)	0.004*
Drought	0.840 (0.321)	0.009*	1.293 (0.552)	0.047**
Household size	-0.085 (0.041)	0.039**	-0.138 (0.072)	0.092***
Off-farm activities	0.306 (0.284)	0.280 NS	0.524 (0.539)	0.359 NS
Experience	-0.265 (0.133)	0.047**	-0.068 (0.061)	0.297 NS
Extension contact	-0.053 (0.081)	0.516 NS	-0.172 (0.583)	0.776 NS
Microfinance credit	-0.683 (0.242)	0.005*	-	-
Chi-square	0.07		0.06	
Pseudo likelihood	-132.37		-966.78	

Note: *, ** and *** denotes 1, 5 and 10% levels of significance. NS denotes insignificant variables

Conclusion

This study estimated the impact of microfinance on the efficiency of maize producers (CB and NCB) in North-Eastern Nigeria. Among the two groups of farmers, CB is more efficient with TE scores of 0.79. On the other hand, NCB is the less efficient group with TE scores of 0.69. The higher TE scores recorded by CB indicated that microfinance credit increases their efficiency by facilitating the purchase of more production inputs at the appropriate time and enable them to adopt enhanced farming techniques than NCB. The results from slacks analysis indicates that all the inputs used in the production processes of the two different groups of farmers contain slacks, which need to be reduced accordingly. Fertilizer, being the major input in maize production and constituting over half of the production costs is similarly over-utilized. The slacks analysis implies that appropriate input targets for inefficient farms can be set to enable them attain optimum technical efficiency in comparison with the most technically efficient farms.

Moreover, technical efficiency results show that all the maize farms in the study area are operating below the production frontier. Therefore, the need to examine the sources of this technical in efficiency by regressing the estimated TE values against some farmers' demographic variables, farm specific and institutional variables. The results designate that household size, years of farming experience and education level increases efficiency whereas drought and age decreases technical efficiency in maize farming. This implies that farmers who have long experience, large household size in maize farming with more educational level were operating closer to the production frontier technology (technically efficient). However, the negative sign and significance of microfinance variable indicates that an increase in the amount of credit given to farmers will likely reduce their technical inefficiency by about 0.683. Therefore, microfinance credit has positive impact on the technical efficiency of the borrowers as it support them to acquire production inputs such as fertilizer, high quality seed, land and agrochemicals appropriately.

Based on these findings, NCB should be inspired to collect loan as well in order to expand their scale of operations and income since it is evident that the higher efficiency level realized by CB was made possible by the loan obtained from microfinance banks. Experience maize farmers should also be encouraged by government through organizing training and workshops to share their maize farming skills with new and young farmers in order to boost their knowledge and increase their efficiency level. Thus, government in collaboration with research institutes and universities should educate farmers on the recommended amount of inputs to apply on their farm lands. This could help them to reduce inputs wastage and production costs thereby increasing the farmers' profit and provide the much needed maize to consumers at a reasonable price.

Nevertheless, this paper investigated the determinants of technical inefficiency in maize production using only eight variables. Hence, future research should reflect factors such as distance to farm area, distance to market, marital status, access to government subsidies and adaptation of improved technology as this may have influence on technical in efficiency. Despite its limitations, the study contributes to literature on technical efficiency in maize production.

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Author's Contributions

Muhammad Auwal Ahmed: He preferred the draft of this manuscript.

Zainalabidin Mohamed: He assisted in technical aspects such as data analysis and ensure accurate interpretation of results.

Abdullahi Iliyasu: He was the one who did the data analysis on technical efficiency and assisted in interpretation of slack variables.

Golnaz Rezai: She played an important role in preparations of the manuscript draft.

Ethics

This article is original and contains unpublished material. The corresponding author confirms that all of the other authors have read and approved the manuscript and no ethical issues involved.

References

Adams, S. and T. Barthlomew, 2010. The impact of microfinance on maize farmers in nkoranza (Brong Ahafo Region of Ghana). J. Manage. Res., 2: 1-13.

Addai, K.N. and V. Owusu, 2014. Technical efficiency of maize farmers across various agro ecological zones of Ghana. J. Agric. Environ. Sci., 3: 149-172.

Ajao, A.O., J.O. Ajetomobi and L.O. Olarinde, 2005. Comparative efficiency of mechanized and non-mechanized farms in OYO state of Nigeria: A stochastic frontier approach. J. Hum. Ecol., 18: 27-30.

Alam, F., 2011. Measuring technical, allocative and cost efficiency of pangas (Pangasius hypophthalmus: Sauvage 1878) fish farmers of Bangladesh. Aquac. Res., 42: 1487-1500. DOI: 10.1111/j.1365-2109.2010.02741.x

Alene, A.D. and R.M. Hassan, 2006. Erratum: The efficiency of traditional and hybrid maize production in Eastern Ethiopia: An extended efficiency decomposition approach. J. African Econ., 15: 91-116. DOI: 10.1093/jae/eji017

Alene, A.D., V.M. Manyong, G.O. Omanya, H.D. Mignouna and M. Bokanga *et al*., 2008. Economic efficiency and supply response of women as farm managers: Comparative evidence from Western Kenya. World Dev., 36: 1247-1260. DOI: 10.1016/j.worlddev.2007.06.015

Ansah, I.G.K., 2014. A comparative analysis of profit efficiency in maize and cowpea production in the ejura sekyedumase district of the Ashanti region, Ghana. Res. Applied Econ., 6: 106-106. DOI: 10.5296/rae.v6i4.6320

Ashaolu, O., S. Momoh, B.B. Phillip and I.A. Tijani 2011. Microcredit effect on agricultural productivity: A comparative analysis of rural farmers in Ogun State, Nigeria. Int. J. Applied Agric. Apic. Res., 7: 23-35.

Ayaz, S., S. Anwar, M.H. Sial and Z. Hussain, 2011. Role of agricultural credit on production efficiency of farming sector in Pakistan-A data envelopment analysis. Pak. J. Life Soc. Sci., 9: 38-44.

Charnes, A., W.W. Cooper and E. Rhodes, 1978. Measuring the efficiency of decision making units. European J. Operat. Res., 2: 429-444. DOI: 10.1016/0377-2217(78)90138-8

Coelli, T.J., D.S.P. Rao and G.E. Battese, 1998. An Introduction to Efficiency and Productivity Analysis. 1st Edn., Kluwer Academic Publishers, Boston, ISBN-10: 0792380606, pp: 275.

Coelli, T.J., D.S.P. Rao and G.E. Battese, 1997. An Introduction to Efficiency and Productivity Analysis. 1st Edn., Springer Science and Business Media, Boston, ISBN-10: 0792380622, pp: 276.

Cooper, W.W., L.M. Seiford and K. Tone, 2000. Data Envelopment Analysis: A Comprehensive Text with Models Applications References and DEA-Solver Software. 1st Edn., Springer Science and Business Media, Boston, ISBN-10: 0792386930, pp: 318.

Dangwa, C.N., 2011. A comparative analysis of maize technical efficiency between a1 resettlement areas and communal areas in Goromonzi district, Mashonaland East province. Doctoral dissertation, University of Zimbabwe.

FAOSTAT, 2016. A database of the Food and Agriculture Organisation of the United Nations (FAO).

FAOSTAT, 2015. A database of the Food and Agriculture Organisation of the United Nations (FAO).

Farrell, M.J., 1957. The measurement of productive efficiency. J. Royal Stat. Society. Series General, 120: 253-290. DOI: 10.2307/2343100

Fekadu, G. and E. Bezabih, 2009. Analysis of technical efficiency of wheat production: A study in Machakel Woreda, Ethiopia. Ethiopian J. Agric. Econom., 7: 1-33.

Feng, S., 2008. Land rental, off-farm employment and technical efficiency of farm households in Jiangxi Province, China. NJAS-Wageningen. J. Life Sci., 55: 363-378. DOI: 10.1016/s1573-5214(08)80026-7

Fukuyama, H. and W.L. Weber, 2009. A directional slacks-based measure of technical inefficiency. Socio-Econ. Plann. Sci., 43: 274-287. DOI: 10.1016/j.seps.2008.12.001

Heady, P. and M. Kohli, 2010. Family, Kinship and State in Contemporary Europe, Volume 3. 1st Edn., Campus, Frankfurt, M. New York, ISBN-10: 3593389630, pp: 451.

Hoff, A., 2007. Second stage DEA: Comparison of Approaches for Modelling the DEA score. Eur. J. Operat. Res., 181: 425-435. DOI: 10.1016/j.ejor.2006.05.019

Ibrahim, K., M.N. Shamsudin, R. Yacob and A.B. Radam, 2014. Technical efficiency in maize production and its determinants: A survey of farms across agro ecological zones in Northern Nigeria. Trends Agric. Econ., 7: 57-68. DOI: 10.3923/tae.2014.57.68

Iliyasu, A. and Z.A. Mohamed, 2015. Technical efficiency of tank culture systems in peninsular Malaysia: An application of data envelopment analysis. Aquac. Econ. Manage., 19: 372-386. DOI: 10.1080/13657305.2015.1082118

Iliyasu, A., Z.A. Mohamed and R. Terano, 2016. Comparative analysis of technical efficiency for different production culture systems and species of freshwater aquaculture in Peninsular Malaysia. Aquac. Rep., 3: 51-57. DOI: 10.1016/j.aqrep.2015.12.001

Ismaila, U., A.S. Gana, N.M. Tswanya and D. Dogara, 2010. Cereals production in Nigeria: Problems, constraints and opportunities for betterment. African J. Agric. Res., 5: 1341-1350. DOI: 10.5897/AJAR09.407

Kidane, A. and E.T. Ngeh, 2015. A comparative analysis of technical efficiency of smallholder tobacco and maize farmers in Tabora, Tanzania. J. Dev. Agric. Econ., 7: 72-79. DOI: 10.5897/jdae2014.0616

Martey, E., A.N. Wiredu and P.M. Etwire., 2015. Impact of credit on technical efficiency of maize producing households in Northern Ghana. Proceedings of the Centre for the Study of African Economies (CSAE) Conference, Mar. 22-24, University of Oxford, pp: 1-25.

McDonald, J., 2009. Using least squares and to bit in second stage DEA efficiency analyses. Eur. J. Operat. Res., 197: 792-798. DOI: 10.1016/j.ejor.2008.07.039

Nuhu, E., A. Inusah, G.R. Ama and Z.M. Sano, 2014. Impact analysis of microfinance on crop production in Ghana. Int. J. Acad. Res. Account. Finance Manage. Sci., 4: 97-108. DOI: 10.6007/ijarafms/v4-i3/1025

Olarinde, L.O., 2011. Analysis of Technical Efficiency Differentials among Maize Farmers in Nigeria. 1st Edn., African Economic Research Consortium, Nairobi, ISBN-10: 9966023046, pp: 34.

Oyewo, I.O., M.O. Rauf, F. Ogunwole and S.O. Balogun, 2009. Determinant of maize production among maize farmers in Ogbomoso South Local Government in Oyo State. Agric. J., 4: 144-149.

Papke, L.E and J.M. Wooldridge, 1996. Econometric methods for fractional response Variables with an application to 401(k) plan participation rates. J. Applied Econometrics, 11: 619-632.

Paudel, P. and A. Matsuoka, 2009. Cost efficiency estimates of maize production in Nepal: A case study of the Chitwan district. Agric. Econom., 55: 139-148.

Ramalho, E.A., J.J. Ramalho and P.D. Henriques, 2010. Fractional regression models for second stage DEA efficiency analyses. J. Productivity Anal., 34: 239-255. DOI: 10.1007/s11123-010-0184-0

Ray, S.C., 2004. Data Envelopment Analysis: Theory and Techniques for Economics and Operations Research. 1st Edn., Cambridge University Press, ISBN-10: 1139453319.

Sihlongonyane, M.B., M.B. Masuku and A. Belete, 2014. Economic efficiency of maize production in Swaziland: The case of Hhohho, Manzini and Shiselweni Regions. Res. Applied Econom, 6: 179-195. DOI: 10.5296/rae.v6i3.6045

Sossou, C.H., F. Noma and J.A. Yabi, 2014. Rural credit and farms efficiency: Modelling farmers credit allocation decisions, Evidences from Benin. Econom. Res. Int., 3: 1-8. DOI: 10.1155/2014/309352

Tone, K., 2001. A slacks-based measure of efficiency in data envelopment analysis. Eur. J. Operat. Res., 130: 498-509. DOI: 10.1016/s0377-2217(99)00407-5

Yamane, T.I., 1967. Statistics: An Introductory Analysis. 2nd Edn., Harper and Row, New York, pp: 919.

Zhou, P., B.W. Ang and H. Wang, 2012. Energy and CO_2 emission performance in electricity generation: A non-radial directional distance function approach. Eur. J. Operat. Res., 221: 625-635. DOI: 10.1016/j.ejor.2012.04.022

Zhou, P., K.L. Poh and B.W. Ang, 2007. A non-radial DEA approach to measuring environmental performance. Eur. J. Operat. Res., 178: 1-9. DOI: 10.1016/j.ejor.2006.04.038