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Analysis of Production Efficiency Among Micro-Credit and Non-Credit Smallholder Maize Growers in Nigeria

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ABSTRACT

Smallholder farmers in Nigeria produce about 90% of the total maize supply, but the production has declined over the last decades due to lack of funding and rising poverty level. Micro-credit as an alternative means of providing financial services to the farmers has the potential to boost their income and facilitate the purchase of farm inputs which could eventually increase their efficiency and output level. Assessment of production efficiency offers valuable insight of the maize farms' performance in terms of resource utilization through which, effective management policies could be framed. This study therefore, determines and compares the production efficiency among micro-credit borrowers and non-borrowers smallholder maize growers in Nigeria. Data was collected using a cross-sectional survey of maize growers during 2016 cropping season via multi-stage sampling technique. Analytical techniques used to analyze the information were descriptive analysis, Data Envelopment Analysis (DEA), Tobit model and t-test. The results show that micro-credit borrowers achieved a respective mean technical, allocative and economic efficiency of 92%, 61% and 59% whereas non-microcredit borrowers achieved only 81%, 51% and 47% respectively. This indicated the presence of considerable resource used inefficiency among the two groups of smallholder maize farmers. Given the existing resources both micro-credit and non-credit borrowers could increase their respective technical efficiency levels by 8% and 19% whereas they could reduce their corresponding costs of production by 39% and 49%. However, the returns to scale results indicated that majority of the farms of credit borrowers (80%) and non-borrowers (91%) were respectively operating under increasing returns to scale (IRS), implying that providing more production inputs to the farmers would lead to more than a proportionate increase in maize output. Findings of pooled data of micro-credit and non-micro-credit maize growers revealed that age of the farmers, education, experience, micro-credit and household size influences efficiency. T-test results indicated that technical, allocative and economic efficiencies between micro-credit borrowers and non-borrowers were statistically significant at 1% level of probability (P<0.01). In conclusion, the results indicate that micro-credit have positive impact on the overall efficiency and output levels of the borrowers as it empower them to acquire more production inputs and utilized it at the appropriate time.

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INTRODUCTION

Maize (*Zea mays* L.) is a staple food of great socio-economic importance and considered as one of the most important cereal crops grown in all the ecological zones of Nigeria. In the year 2014 for instance, about 5.9 million hectares of land were allocated to maize production alone and as a result 7.5 million tons was realized. Nigeria has a potential for maize production which accounts for about 46.24% of all the maize grown in West and Central Africa (FAO, 2015). However, the production has failed to bridge the increasing supply-demand gap which presents a challenge to the growing population of Nigeria especially in the north where it is being consumed largely in the form of corn flour and corn grits. Despite the frantic efforts made by government through the introduction of new varieties of seeds and seedlings, fertilizer subsidy by 25%, introduction of zero tariffs on imported agrochemicals, maize output is still low, averaging only 2.0 metric tons/ha (Ibrahim *et al*., 2014). Majority of the country's farms (over 90%) belongs to smallholder farmers who produced 70% of the country's total output, but unfortunately they are confronted with inadequate capital base, restricted access to credit due to low income and managerial problems that affect their efficiency and output level.

The argument reported by many empirical studies (Girabi and Mwakaje, 2013; Sossou *et al*., 2014; Martey *et al*., 2015) has been very reliable in terms of using microfinance to increase crop production and the living standard of credit beneficiaries since the credit beneficiaries are better off in assessing farm inputs, markets for their produce and adoption of improved farming skills than those without credit. An understanding of the levels of production efficiency and its relationship with a host of farm level factors can help policy makers mainly in forming efficiency enhancing programs as well as in judging the effectiveness of the existing and previous reforms.

Literature Review:

Many empirical studies have estimated agricultural productivity around the world, but only a few focused on maize production efficiency. For example, Martey *et al*. (2015) determines the impact of credit on smallholders' technical efficiency of maize producing households in northern Ghana and reported that credit had positive impact on the technical efficiency of farmers and that the mean efficiency scores attained by credit beneficiaries was 62% whereas non-credit beneficiaries obtained about 53%. Sossou *et al*. (2014) examines farmers' credit allocation behaviors and their effects on technical efficiency in Benin. The findings reveal that spending credit in obtaining farm inputs has positive impact on technical efficiency and farm revenue of the borrowers, while Ayaz *et al*. (2012) examines the role of agricultural credit on production efficiency of farming sector in Faisalabad, Pakistan. The results signify that farmers achieved an average technical efficiency score of about 78% showing 22% level of inefficiency among the sample farmers. The findings also revealed that education, herd size, years of experience in farming, access to farm credit and number of farming practices had significant effect on the technical efficiency level of farmers. Likewise, Esham (2014) analyzed technical efficiency of maize production by smallholder farmers in the Moneragala district of Sri Lanka and his findings indicated that the mean technical efficiency of the farmers was 72%, while Essilfie *et al*. (2011) estimated farm level technical efficiency of small scale maize production in the Mfantseman Municipality, Ghana and discovered that the technical efficiency scores ranges from 0.17 to 0.99 with an average of 58%.

Furthermore, Addai and Owusu (2014) analyzed technical efficiency of maize farmers across various agro ecological zones of Ghana. They observed that the average technical efficiency of the sampled maize farms across the three agro ecological zones was 64%, while the average technical efficiency in the savannah, forest, and transitional zones were 52%, 80% and 61% respectively. Their findings also indicated that gender, access to credit, extension; age, mono cropping and land ownership had positive impact on technical efficiency. Ahmed *et al*. (2014) also studied technical efficiency of smallholder maize farmers in central rift valley of Ethiopia. Their results show that farmers attained a slightly higher mean technical efficiency of 88%. Mango *et al*. (2015) estimated technical efficiency of smallholder maize production in Zimbabwe. Their findings show that maize output reacts positively to increases in the quantity of seeds, inorganic fertilizers, man-days of labour and the area cultivated and that about 90% of the farms had efficiency index of between 60% and 75% with an average of 65%. Equally, Sihlongonyane *et al*. (2014) determined economic efficiency of maize production in Hhohho, Manzini and Shiselweni Regions of Swaziland. The study revealed that the respective mean technical, allocative and economic efficiencies were 65%, 99% and 64%.

Nevertheless, the findings of the studies indicate that a considerable level of inefficiency exists and that farmers could improve their efficiency levels if resources are properly harnessed and utilized. There is also no doubt that none of the preceding studies operated at the frontier technology (100%) and as such, this study apply input-oriented DEA model to estimate and compare the production efficiency among micro-credit borrowers and non-borrowers smallholder maize growers in Nigeria. In this study, the relationship between efficiency level and several farm specific and institutional factors has been determined as well.

Conceptual framework:

The conceptual framework for determining efficiency could be introduced by considering a firm that is producing one output (Y) from two variable inputs (X_1 and X_2). The points G, H, I and R in figure below represents five firms with different inputs combinations in production. To determine the efficiency of any firm, the reference standard has to be defined. By using the actual observations and drawing straight lines between the observations closest to the axis, we can envelope the observation to construct the frontier A-A^1. The firms G, H and I are apparently the most efficient firms. They represent the best practice and can serve as reference standard for other firms (figure 1).

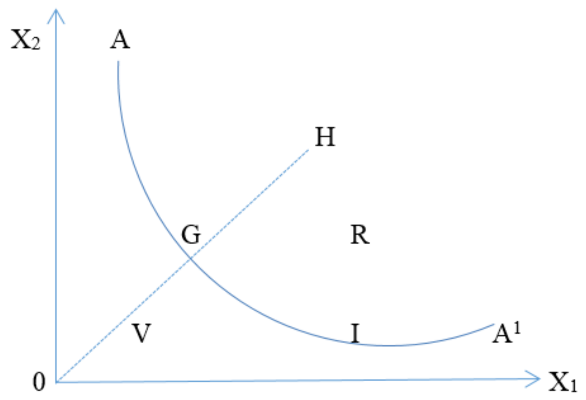

Figure 1: Measure of technical efficiency
Source: (Adapted from Coelli, 1996) .

Though, it is obvious that no firm will produce at point V, which is below the frontier line A-A^1 because producing at this point will not be technically feasible. A firm producing above A-A^1 line such as H will be technically inefficient because at point G, the same output will be produce with the same factor ratio. Farrell proposed that the technical efficiency (TE) of a firm at point H, is most commonly measured by the ratio TE_1= OG/OH, Which is equal to 1-GH/OH. It will take a value of between zero and one, and hence display the degree of technical inefficiency of the firm. A value of one indicates that the firm is highly technically efficient such as point G which lies on the efficient isoquant. The allocative efficiency of the firm operating at point H is calculated as the ratio AE_1= OV/OG. The overall economic efficiency (EE_1) is defined as the ratio EE_1= OV/OH, where the distance VH can also be interpreted in terms of cost reduction. The product of technical and allocative efficiency provides the overall economic efficiency as follows; $TE_1 \times AE_1$ = (OG/OH) (OV/OG) = OV/OH = EE_1. All the three measures are bounded by zero and one.

Methodology:

Study Area:

The study was conducted in Adamawa and Bauchi States of North-Eastern Nigeria. The area has an annual rainfall of between 700 mm and 1,550 mm and has between three to six months of rainfall a year, with August and September as the wettest months, while the driest months are February and March with relative humidity of about 37% [Nigerian Meteorological Agency (NiMet, 2015)]. Agriculture is the source of occupation to a majority of the population through subsistence traditional farming system in the study area.

Data Collection:

Data used for the study was collected from a cross-sectional survey of smallholder maize growers during 2016 cropping season using a multi-stage sampling technique. In the first stage, Adamawa and Bauchi states were selected due to the prevalence of poverty and their prominence in agricultural potential as well as the existence of micro-credit institutions (Kale, 2012; NBS, 2015). This is followed by the selection of Jada, Furfore, Dass and Katagum LGAs based on the prominence of microfinance and maize farming activities. The sample of credit borrowers were randomly selected from the lists of borrowers collected from the microfinance banks offices situated in each of the surveyed local government headquarters. The lists of non-borrowers were obtained from the department of agricultural development projects of each LGA to provide a control group for comparison with borrowers. Finally, a total of 179 farmers were selected from a sampling frame of 550 registered farmers of which 98 of them were the micro-credit borrowers whereas the remaining 81 farmers were the non-credit borrowers. However, the table for determining sample size needed to be representative of a given population of Krejcie and Morgan (1970) was used in estimating the required sample size for the study.

Analytical Technique:

The study employed the nonparametric mathematical programming approach, commonly known as data envelopment analysis (DEA) as used by Charnes *et al*. (1978) and Fare *et al*. (1994) to analyze the data. DEA is based on multiple-input, multiple-output relation in which linear programming is used to construct a non-parametric piecewise surface (frontier) around the data (Charnes *et al*., 1995). It tries to maximize the relative technical efficiency score of each decision-making unit by minimizing input (the input-oriented efficiency model) or maximizing output (the output-oriented efficiency model). DEA analyzes technical efficiency under the assumption of either constant returns to scale (CRS) or variable returns to scale (VRS). However, in the maximization process, farms always face financial limitations or imperfect competitive markets where increased amounts of inputs do not proportionally increase the amount of outputs obtained (Coelli *et al*., 2005). In order to account for these effects the DEA model for variable returns to scale (VRS) was developed by Banker *et al*. (1984) and used by Ibrahim *et al*. (2014) and Iliyasu *et al*. (2016). This study therefore, employed the VRS approach in the data analysis.

The DEA model under VRS assumption for each farm is defined by the linear program of the form:

$$\mathrm{M}ax\ \Phi\beta\phi \tag{1}$$

Subject to X_i - $\mathrm{X}\beta \geq 0$

$$-\phi\ y_i + \mathrm{Y}\beta \geq 0$$

$$\mathrm{N1}'\ \beta = 1$$

$$\beta \geq 0$$

Where; *N1'* is a convexity constraint which is an $N \times 1$ vector of ones and β is an $N \times 1$ vector of weights (constant) which defines the linear combination of the peers of the h^{th} farm.

Similarly, to estimate economic efficiency scores, a cost minimizing DEA model is specified as follows:

$$\mathrm{M}in_{\ \beta,\chi_i^*}\ C_i^* h_i' \tag{2}$$

Subject to:

$$-y_i + \mathrm{Y}\beta \geq 0$$

$$h_i^* - h\beta \geq 0$$

$$N1'\ \beta = 1$$

$$\beta \geq 0$$

Where; C_i is a transpose vector of input prices for the h^{th} farm and h_i^* is the cost-minimizing vector of input quantities for the h^{th} farm given the input prices C_i and total output level y_i. Following the definition of Farrell (1957), AE is calculated as the ratio of EE to TE i.e.

$$AE_i = \frac{\mathrm{EE}_i}{\mathrm{TE}_i} \tag{3}$$

Given that VRS type is the production technology, scale efficiency (SE) measure can be obtained by estimating both a CRS and VRS DEA models represented by the following formula (Coelli *et al*., 2005):

$$SE_i = \frac{T\mathrm{E}_{CRS}}{\mathrm{TE}_{VRS}} \tag{4}$$

Where; $0 \leq SE \leq 1,$

When SE = 1, represents constant returns to scale (CRS), SE < 1, signifies increasing returns to scale (IRS) and SE > 1, implies decreasing returns to scale (DRS).

Definition of Variables:

The inputs and outputs variables and the costs related with each input under consideration were estimated using DEAP version 2.1 as described in Coelli (1996).

These variables include:

Y_i = maize output in kilogram (kg/ha)

X_1 = fertilizer used (kg/ha)

X_2 = quantity of seeds (kg/ha)

X_3 = labour (man-days/ha)

X_4 = agrochemicals used (liters/ha)
P_1 = cost of fertilizer (USD/ha)
P_2 = cost of labour (USD/ha)
P_3 = cost of agrochemicals (USD/ha)
P_4 = cost of seeds (USD/ha)

Maize output referred to the total yield produced by each farmer weighted in kg/hectare (Y_i). Fertilizer include inorganic fertilizer used and is measured in kg/hectare (X_1). Quantity of seeds include seeds planted for maize cultivation and was measured in kg/ha (X_2). Labour is considered as one of the important human capitals which empower farmers to achieve their livelihood goals. In the context of rural Nigeria, farming activities are poorly mechanized. Therefore, farmers depend on both family and hired labour for pursuing their farm activities. In this study as well, both family and hired labour were utilized during the production period and is measured in man-days/ha (X_3). Quantity of agrochemicals represents the amount of chemicals used on maize farm and is measured in liter/ha (X_4).

P_1 represents the amount of money spent on seeds used during planting which is measured in USD/ha. P_2 is the costs of both hired and imputed labour per day measured in USD/ha. P_3 represents the amount spent on agrochemicals during the production period and it was measured in USD/ha, while P_4 referred to the money spent on purchasing fertilizer used during cultivation and it was measured in USD/ha.

Two-limit Tobit Model:

Tobit model is used on the assumption that efficiency scores are bounded by zero and unity with the upper limit set at one implying that the distribution is censored at both tales ($0 < U_i < 1$). When a variable is censored, OLS will yield inconsistent, inefficient and biased estimates because it underestimates the true effect of the parameters by reducing the slope (Gujurati, 2003). Hence this study adopts two-limit Tobit regression model approach (Tobin, 1958), to estimate the causes of inefficiency in the study area.

The model is expressed as below:

$$U_i^* = \beta_0 + \sum_{s=1}^{k} \beta_s Z_{is} + \mu_i,$$
$$U_i = \{0 < U_i < 1\} \qquad (5)$$
$$U_i = 0 \ \{\text{if}, U_i \geq 0\}$$

Where: i = refers to the i^{th} farm, U_i^* = the inefficiency estimates of the i^{th} farm, β_s are the estimated parameters and μ_i = error term. Z_{is} are the variables and the model can be specified in its explicit form as:

$$lnU_i = \beta_0 + \beta_1 lnZ_1 + \beta_2 lnZ_2 + \beta_3 lnZ_4 + \cdots + \beta_7 lnZ_7 + \varepsilon_i \qquad (6)$$

Z_1 = Credit (dummy, 1 = credit, 0 = otherwise)
Z_2 = Education (dummy: 1= educated, 0 = otherwise)
Z_3 = Household size (number of people per household)
Z_5 = Age (years)
Z_6 = Experience (years)
Z_7 = Extension contact (dummy: 1 = yes, 0 = otherwise)

RESULTS AND DISCUSSION

Descriptive Statistics of Data used for DEA:

Descriptive statistics of data used for efficiency estimation of smallholder maize farmers who were credit borrowers and non-borrowers are presented in Table 1. The data shows that an average farmer who borrows credit produces 1,508.01kg of maize per hectare. The data also shows that the average quantity of inputs used by a credit borrower per hectare was 108.48kg of fertilizer, 16.71kg of seeds, 15.83 man/days of labour and 3.35 liters of agrochemicals whereas the average costs of fertilizer, labour, agrochemicals and seeds were estimated at \$28.87, \$91.27, \$12.11 and \$15.31 respectively.

On the other hand, the data indicates that an average farmer who was not involved in borrowing from micro-credit institutions produces 1,010.21kg of maize per hectare. The average quantity of inputs used per hectare were 75.56kg of fertilizer, 8.73 man/days of labour, 2.10 liters of agrochemicals and 12.79kg of seeds with a corresponding cost of \$6.66, \$5.54, \$3.60 and \$3.27.

Table 1: Descriptive Statistics of Credit Borrowers and Non-Credit Borrowers

DEA Variables	Variables Description	Unit of Measurement	(C=98) Mean	SD	(NC=81) Mean	SD
	Output Variable					
Y_i	Maize output	Kilogram	1,508.01	281.10	1,010.21	229.31
	Input Variables					
Z_1	Fertilizer	Kilogram	108.48	29.60	75.56	20.22
Z_2	Labour	Man/days	15.83	3.51	8.73	2.10
Z_3	Agrochemicals	Liters	3.35	0.94	2.10	0.67
Z_4	Seeds	Kilogram	16.71	2.19	12.79	1.27
	Input Costs					
P_1	Fertilizer Cost	USD ($)	4,475.10	2,287.19	3,263.26	1,031.73
P_2	Labour Cost	USD ($)	14,146.66	4,864.68	10,833.0	858.49
P_3	Agrochemical Cost	USD ($)	1,877.72	822.93	907.21	558.10
P_4	Seeds Cost	USD ($)	2,373.32	851.43	1,242.21	506.30

Source: Field Survey, 2016
NB: C = Credit (n=98), while NC = Non-Credit (n=81)

Distribution of TE, AE and EE Estimates of Credit and Non-Credit Borrowers:

Tables 2 and 3 present the distribution of TE, AE and EE estimates of micro-credit and non-credit borrowers among smallholder maize farmers. The estimated TE for micro-credit borrowers shows that the best practicing farm operated at 1.00. This implies that the farm has attained the highest point of efficiency being the frontier technology whereas the least were found to operate at about 62% with a mean efficiency level of 92%. Similarly, the TE scores of non-credit borrowers range from 0.55 to 1.00 with an average farm operating at about 81%. This indicates that a farmer who collects micro-credit averagely produced about 92% of the maximum desirable output for a given level of inputs, while non-credit borrowers produced about 81%. The results show that both groups can still improve their respective average efficiency levels by about 8% and 19% in order to operate at the frontier. The results is in consistent with similar study conducted by Ahmed *et al*. (2014) who reported that the mean TE of maize producers in central rift valley of Ethiopia was 88%, while on the contrary, Addai and Owusu (2014), Mango *et al*. (2015) reported the mean TE scores of 64% and 65% respectively.

The minimum and maximum AE estimates of micro-credit borrowers were 0.41 and 1.00 whereas non-credit borrowers recorded about 0.30 and 1.00 respectively. This means that there is a great variation between the least and the best allocatively efficient farm. The findings show that the mean AE of both groups were 61% and 51% respectively. This implies that farmers have the potential to reduce their costs of production by about 39% and 49% in order to be allocatively efficient. The inference drown from each of the models indicates that some inputs are being used in an incorrect proportions. The result corroborates with the findings of Aye and Mungatana (2012) who also reported that the mean AE scores obtained by maize farmers was 53%.

The EE estimates (Tables 2 and 3) of micro-credit borrowers ranges from 0.31 to 1.00 whereas non-borrowers had 0.21 to 1.00, indicating a huge difference between the worse and the best economically efficient farm in the study area. The average EE of micro-credit borrowers is 59%, while non-credit borrowers recorded only 47% implying that more than 41% and 53% of the farms in each group were operating below the average EE which is far from the production frontier. The findings deduced that micro-credit borrowers and non-borrowers were unable to use minimum inputs and minimum costs for a given level of output. However, farmers could still increase their economic efficiency by 41% and 53% in order to operate at the optimum level and becomes economically efficient. The results support the findings of Sihlongonyane *et al*. (2014), who also reported that maize farmers could increase their economic efficiency by 49% and 36% respectively. However, the higher yields and efficiency estimates recorded by micro-credit borrowers was made possible because of their ability to obtained credit and invest more in their production activities. Similar results were also reported by (Girabi and Mwakaje, 2013; Martey *et al*., 2015). Thus, findings of both micro-credit borrowers and non-borrowers have demonstrated that maize farmers in north eastern Nigeria operates with great inefficiency and this offers an avenue for policy interventions that would help to mitigate the inefficiency and becomes as efficient as those that operated on the frontier technology.

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Table 2: Technical, Allocative and Economic Efficiency Estimates of Credit Borrowers

Efficiency Range	TE		AE		EE	
	Frequency	percent	Frequency	Percent	Frequency	Percent
0.21 ≤ 0.30	-	-	-	-	-	-
0.31 ≤ 0.40	-	-	-	-	5	5.10
0.41 ≤ 0.50	-	-	17	17.35	26	26.53
0.51 ≤ 0.60	-	-	30	30.61	23	23.47
0.61 ≤ 0.70	10	10.20	20	20.41	18	18.37
0.71 ≤ 0.80	31	31.63	14	14.29	11	11.23
0.81 ≤ 0.90	28	28.57	10	10.20	9	9.18
0.91 ≤ 1.00	29	29.60	7	7.14	6	6.12
Total	98	100.0	98	100.0	98	100.0
Mean	0.92		0.61		0.59	
Minimum	0.62		0.41		0.31	
Maximum	1.00		1.00		1.00	

Source: Field Survey, 2016

Table 3: Technical, Allocative and Economic Efficiency Estimates of Non-Borrowers

Efficiency Range	TE		AE		EE	
	Frequency	percent	Frequency	Percent	Frequency	Percent
0.21 ≤ 0.30	-	-	-	-	15	18.50
0.31 ≤ 0.40	-	-	26	32.10	22	27.20
0.41 ≤ 0.50	-	-	14	17.30	15	18.50
0.51 ≤ 0.60	5	6.17	17	21.00	11	13.60
0.61 ≤ 0.70	12	14.81	10	12.30	8	9.90
0.71 ≤ 0.80	6	7.41	5	6.20	4	4.90
0.81 ≤ 0.90	20	24.70	5	6.20	2	2.50
0.91 ≤ 1.00	38	46.91	4	4.90	4	4.90
Total	81	100.0	81	100.0	81	100.0
Mean	0.81		0.51		0.47	
Minimum	0.55		0.30		0.21	
Maximum	1.00		1.00		1.00	

Distribution of Farms Based on Returns to Scale Operation:

As shown in Table 4, the distribution of scale efficiency on the basis of returns to scale reveals that 79.59% and 91.36% of micro-credit borrowers and non-borrowers were respectively operating under increasing returns to scale (IRS), 14.29% and 2.47% operated at decreasing returns to scale (DRS), while 6% and 6.17% operated at constant returns to scale (CRS) respectively. Since majority (79.59% and 91.36%) of the farmers in both groups were operating under IRS, this means that providing more production inputs to the farmers would lead to more than proportionate increase in the eventual maize output.

Table 4: Distribution of Farms Based on Returns to Scale Operations

Returns to scale	Frequency (Borrowers)	Percent	Frequency (Non-Borrowers)	Percent
IRS	78	79.59	74	91.36
DRS	14	14.29	2	2.47
CRS	6	6.12	5	6.17
Total	98	100	81	100

Source: Field Survey, 2016

T-test Results of Micro-Credit Borrowers and Non-Borrowers:

The t-test results presented in Table 5 revealed that maize output, TE, AE and EE estimates of micro-credit borrowers differ greatly from non-borrowers at 1% level of probability ($P < 0.01$). The results show that micro-credit borrowers gained greater output with a mean difference of 497.80kg/ha than the non-credit borrowers. Also, farmers who received micro-credit tend to be more efficient in terms of TE, AE and EE with a mean difference of about 11%, 10% and 12% respectively during the cropping season. The difference in means could be attributed to the fact that micro-credit borrowers have more money at their disposal made possible by the loan borrowed from microfinance banks which enable them to purchase more production inputs and invest in their farm lands whereas non-borrowers do not have more money probably due to the prevalence of poverty in the area and therefore could not afford to buy more inputs for their production. Besides, empirical literatures on the impact of micro-credit on maize production indicates that access to credit can improve the farmers' productivity and income which could have positive impact on their well-being (Ambali *et al*., 2012; Girabi and Mwakaje, 2013; Martey *et al*., 2015).

Table 5: T-test Results for Credit Borrowers and Non-Borrowers

Variables	Borrowers (n=98)	Non-Borrowers (n=81)	Mean Difference	T-value	P-value
	Mean	Mean			
Maize Output	1,508.01	1,010.21	497.80	12.80	0.000*
TE	0.92	0.81	0.11	6.14	0.000*
AE	0.61	0.51	0.10	4.02	0.000*
EE	0.59	0.47	0.12	6.83	0.000*

Source: Field Survey, 2016

Causes of Technical Inefficiency in Maize Production:

In this section, the TE of credit borrowers and non-borrowers were estimated separately using DEAP version 2.1, and their resulting estimates were pooled together along with the causes of inefficiency in the study area. In order to determine the impact of credit on the overall technical efficiency, a dummy value of one is assigned to credit borrowers and zero otherwise. Thus, the two limit Tobit regression model (equation 3) was estimated and the result is presented in Table 6. Generally, a positive sign of a parameter estimate means that the variable increases technical efficiency, while a negative sign reduces technical efficiency. The results in Table 6 shows that age of the farmers, education, farming experience, credit and household size were statistically different from zero at varying levels of probability, whereas off-farm activities and extension contact were not statistically different from zero. However, all the estimated variables carry the expected signs which are desirable.

The coefficient of farmers’ age is positive and statistically significant at 5% level of probability. This means that the more the farmers grow older, the lesser the technical efficiency. This could be attributed to the intensive labour and pressure involves in farming operations and hence, when the farmers grow older, they are most likely to be less efficient. This is also supported by the findings of Mulinga (2013) and Esham (2014). Educational level of farmers is positive and significantly different from zero. This might be because education plays a significant role in skills acquisition and technology transfer. Farmers with higher level of education are likely to be more efficient in the use of inputs than those that are uneducated. This is because knowledge facilitates the adoption and understanding of new techniques and farmers’ ability to plan and avert risks. The result is similar to that of Ayaz *et al*. (2012), Lefophane (2012) and Sihlongonyane *et al*. (2014) who also found out that education increases efficiency.

Years of farming experience is positive and statistically significant at 1% level of probability. This implies that farmers with more years of farming tend to be more efficient in maize production as they might have acquired more skills by learning and doing over the years. The result agrees with the results of Addai and Owusu (2014) and Iliyasu *et al*. (2016) who observed that an increase in the number of years in farming increases technical efficiency. The coefficient of micro-credit was estimated to be positive and statistically different from zero at 1% level. This means that farmers who obtained credit have the tendency to become more efficient than their non-credit borrowers counterparts. This is because credit enables farmers to purchase adequate production inputs and also finance their farming activities which in turn increased their productivity and income. This supports the findings of Sossou *et al*. (2014) and Martey *et al*. (2015) who observed that access to credit improves resource use efficiency. Household size is positive and significant at 1% level, signifying its importance in agricultural production especially in smallholder farming in Nigeria. This is due to the fact that household members serves as the main source of labour and therefore, the more the number of people living in a household, the more the labour supply for carrying out farming operations. This is supported by Iliyasu *et al*. (2016) and Ahmed *et al*. (2016) who mentioned that larger households are more efficient in agricultural production.

The likelihood ratio (LR) chi-square test and log-likelihood are the indicators of the performance of a good Tobit regression model. The likelihood ratio (LR) chi-square test with a corresponding probability value of 0.059 at a specified alpha level set at 0.05 indicates that the model is correctly specified. The log likelihood value of -28.247 is an indication of goodness of fit for the model and the correctness of the distributional assumption of the composite error term.

Table 6: Tobit Regression Results of Pooled Data for Credit Borrowers and Non-Borrowers

Variables	Coefficient	Std. Error	Z-value	P-value
Constant	0.749	0.080	9.36	0.0001*
Micro-credit	0.157	0.025	6.28	0.0001*
Off-farm activities	0.019	0.023	0.83	0.4065^{NS}
Education	0.148	0.027	5.48	0.0001*
Household size	0.218	0.013	16.77	0.0001*
Age	-0.005	0.002	2.50	0.0124**
Experience	0.012	0.002	6.00	0.0001*
Extension contact	0.022	0.027	0.82	0.4122^{NS}
LR Chi-square (Prob)	0.059			
Log likelihood	-28.247			

Note: * and ** denotes 0.01% and 0.05% levels of significance.
^{NS} denotes insignificant variables.

Conclusion:

The study used input-oriented DEA model to estimate TE, AE and EE of smallholder maize farmers in North Eastern Nigeria and compared the efficiency estimates achieved by micro-credit borrowers and non-borrowers. The results show that the mean efficiency estimates of farmers who collected micro-credit was 92%, while non-credit borrowers achieved about 81% level of efficiency. This implies that the efficiency estimates of micro-credit borrowers were generally higher than non-borrowers. However, given the existing resources, micro-credit borrowers and non-borrowers could increase their respective TE levels by 8% and 19% whereas they could reduce their corresponding costs of production by 39% and 49%. The TE estimates of pooled sample data under Tobit model indicates that farmers' age, education, experience, micro-credit and household size increases technical efficiency. Findings of t-tests show that there is a significant difference between the two groups in terms of maize output, TE, AE and EE thereby suggesting that micro-credit have positive influence on the overall efficiency and output levels of the borrowers as it empower them to purchase farm inputs at the proper time.

The main contribution of the study is in determining the production efficiency of maize growers through the use of micro-credit as a tool in order to observe the extent of efficiency variation among credit borrowers and non-borrowers. Similarly, the introduction of micro-credit in maize farming has improved the efficiency and output levels of credit borrowers due to their ability to invest more in their production activities than their non-borrowers counterparts. Analysis of resource use efficiency assists farmers in understanding their efficiency level and the factors responsible for inefficiency in the study area.

The study recommends for easy access to micro-credit loan at subsidized interest rate combined with continued availability of complementary agricultural support services, comprising of extension, on-farm training and raising the educational level of farmers in order to facilitate the transfer and adoption of technologies. This might eventually reduce the inefficiencies faced by the farmers and push them towards the production frontier in the long run leading to improvement in the overall resource use efficiency and productivity. Moreover, efficient use of resources would lead to decrease in costs of production, increases income and general well-being of the farmers.

However, this paper investigated the causes of technical inefficiency in maize production using only seven variables. Hence, future research should reflect factors such as farm size, access to government subsidies, prevalence of drought and adaptation of improved technology as this might have impact on technical inefficiency. This study focused on North Eastern Nigeria due to cost constraint. It is vital for future works to increase their search to cover farming activities in other parts of Nigeria in terms of those who collect micro-credit from the banks and those who did not especially North West and North Central where farming is the main occupation and poverty is prevalent. Despite the limitations, the study still contributes to the current literature on micro-credit and efficiency in maize production.

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