Impact of Microfinance on the Efficiency of Maize Producers in Nigeria

Muhammad Auwal Ahmed, Zainalabidin Mohamed, Abdullahi Iliyasu and Golnaz Rezai

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 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).

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

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

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

Source: (FAOSTAT, 2016)
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 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 of the production possibility set with no doubt that none of the preceding studies operated at the frontier of the production possibility set with no doubt that none of the preceding studies operated at the frontier of the production possibility set with no doubt that none of the preceding studies operated at the frontier of the production possibility set with no doubt that none of the preceding studies operated at the frontier of the production possibility set with no doubt that none of the preceding studies operated at the frontier of the production possibility set with no doubt that none of the preceding studies operated at the frontier of the production possibility set with no doubt that none of the preceding studies operated at the frontier of the production possibility set with no doubt that none of the preceding studies operated at the frontier of the production possibility set with no doubt that none of the preceding studies operated at the frontier of the production possibility set with no doubt that none of the preceding studies operated at the frontier of the production possibility set with no doubt that none of the preceding studies operated at the frontier of the production possibility set with no doubt that none of the preceding studies operated at the frontier of the production possibility set with no doubt that none of the preceding studies operated at the frontier of the production possibility set with no doubt that none of the preceding studies operated at the frontier of the production possibility set with no doubt that none of the preceding studies operated at the frontier of the production possibility set.

**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:

\[ n = \frac{N}{1 + Ne^2} \]  

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 is 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 has 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:

\[
\rho_t = \min \left(1 - \frac{\sum_{i=1}^{m} s_i^r / \lambda s_i^r}{s_{0i}}\right)
\]

Subject to: \(x_i = X \lambda + s_i^r, (i = 1..m)\)

\(y_i = Y \lambda - s_i^r, (r = 1..s)\)

\(\lambda \geq 0, s_i^r \geq 0, s_i^r \geq 0\)

Where:

- \(x_{0i}\) = The amount of input \(i\) used by a particular farm
- \(y_0\) = The amount of output produced by a particular farm
- \(s^r\) = Input slack variables
- \(s^r\) = Output slack variables
- \(m\) = Number of inputs used during production
- \(r\) = Number of output
- \(\rho_t\) = SBM-input-efficiency
- Sub-index \(x_i\) = Cross-sectional data
- Subscript “\(O\)” = The farm whose efficiency is being estimated in the model
- \(\lambda\) = Non-negative multiplier vector used for computing a linear combination of variables

The following condition will hold if a farm is efficient; \(\rho_t^r = 1, \lambda^r = 0, s_i^r = 0\) and \(s_i^r = 0\) (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:

\[
Y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \beta_3 x_{i3} + \ldots + \beta_k x_{ik} + \epsilon_i
\]

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 \([0 < Y < 1]\).
- \(X_{i1}\) = Off-farm activities
- \(X_{i2}\) = Duation
- \(X_{i3}\) = Drought
- \(X_{i4}\) = Household size
- \(X_{i5}\) = Age
- \(X_{i6}\) = Experience
- \(X_{i7}\) = Extension contact
- \(X_{i8}\) = Microfinance credit
- \(\beta_{0-8}\) = Vector of coefficients
- \(\epsilon_i\) = 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 Bezaibih (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

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

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 drawn 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 fertilizers lacks 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
The coefficient of farmers’ experience was found to be negative and statistically significant in both CB and NCB models. 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

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

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

<table>
<thead>
<tr>
<th>Inputs</th>
<th>Slacks (CB)</th>
<th>Frequency</th>
<th>Slacks (NCB)</th>
<th>Frequency</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fertilizer</td>
<td>32.34</td>
<td>98</td>
<td>19.48</td>
<td>83</td>
</tr>
<tr>
<td>Seeds</td>
<td>6.03</td>
<td>17</td>
<td>2.73</td>
<td>69</td>
</tr>
<tr>
<td>Labour</td>
<td>7.79</td>
<td>69</td>
<td>2.54</td>
<td>48</td>
</tr>
<tr>
<td>Agrochemicals</td>
<td>2.44</td>
<td>26</td>
<td>1.76</td>
<td>51</td>
</tr>
<tr>
<td>Total</td>
<td>48.6</td>
<td>-</td>
<td>26.51</td>
<td>-</td>
</tr>
</tbody>
</table>

Source: Computed from field survey, 2015
Table 5. Fractional regression results of CB and NCB

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

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 slack 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 slack 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


