MEASURING THE TECHNICAL EFFICIENCY OF MAIZE PRODUCTION USING PARAMETRIC AND NON-PARAMETRIC METHODS IN OYO STATE, NIGERIA

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ABSTRACT

This study compared Data Envelopment Analysis and Stochastic Frontier Analysis to assess efficiency of maize production using a cross-section data randomly obtained from maize farmers in Ogo-Oluwa Local government Area of Oyo State. Previous studies have dealt with the use of either of the techniques or both. Consistency of potential existence was found in the two approaches but varies in magnitude. The significant variations in the level of inefficiency across sample farms were attributed to the variations in the 'use intensities' of resources.
Keywords: parametric; Stochastic frontier; DEA; technical efficiency;

INTRODUCTION

The agricultural sector has always been an important component of Nigeria's economy with farmers producing over ninety percent (90%) of the food available in the country and about seventy percent (70%) of the entire labour force relying on this sector, with the contribution of about fifty percent (50%) of the Gross Domestic Product and more than seventy-five percent (75%) of export earnings (Okoruwa, 1997). Therefore, effective economic development strategy depends critically on promoting productivity and output growth in the agricultural sector, particularly among smallholder producers which dominate the sector. Small scale farmers are desirable, not only because they provide equitable distribution of income as well as an effective demand structure for other sectors of the economy (Bravo-Ureta and Evenson, 1994).

Maize is one of the popular cereals in Nigeria and serves as the main staple food for millions of Nigerians.. A report has it that it was introduced to Europe in 1942 from Southern and Central America by Christopher Columbus and later spread to Africa (Okoruwa, 1997). Today, maize has become Africa's most important staple food crop and is grown by both large and small scale farmers. Currently, maize is produced in most countries of the world and is the third most planted field crop after wheat and rice. The bulk of maize production occurs in the United States and the Peoples Republic of China (456.2 million tons). Mexico, the world's fourth largest producer of maize currently produces approximately 14 million tons of grain annually on 6.5 million hectares (Ricardo, 1997). Being one of the strategic crops in Nigeria, this study examined the efficiency of maize production in Oyo State, Nigeria. The term efficiency is often used synonymously with that of productivity, the most common measures of which relate output to some single input (Lund and Hill, 1979). According to Lovell (1993), the term efficiency refers to the comparison between the real or observed values of input(s) and output(s) with the optimal values of input(s) and output(s) used in a particular production process. Efficiency is achieved either by minimizing the resources required for producing a given output. Moreover, according to the optimal values, two types of efficiency can be distinguished-technical efficiency and allocative efficiency.

Technical efficiency is considered to be an important determinant of productivity growth and international competitiveness in any economy (Taymaz and Saatci, 1997). It is also considered to be an important factor which contributes to stability of production. There are different schools of thought in estimating the technical efficiencies. A technically efficient firm is the one which produces on production frontier to obtain the maximum possible output which is feasible using current technology (Kalirajan and Tse, 1989). Since this concept resembles that of Friedman theory (1967) that a production functions can reflect the entrepreneurial ability to produce maximum output under given circumstances, thus the technical efficiency of a firm tends to reflect the entrepreneurial efficiency keeping other things constant (Kalirajan and Tse, 1989). The technical efficiency has been defined as the ratio of actual output to potential output given by the frontier production function as defined by Leibenstein (1966) for a given set of inputs and technology.

Taking into account that not all the firms are efficient and the efficient ones have varying levels of efficiency, there arises then the need to measure efficiency as a proxy for firm's performance. The techniques for measuring efficiency are referred to as frontier techniques. Thus, two main approaches can be used to estimate efficiency in a production process; the non-parametric approach and the parametric approach. This non-parametric efficiency measurement method is a mathematical programming approach often referred to as the Data Envelopment Analysis (DEA) (Charnes et al., 1978). DEA uses linear programming methods to estimate a production frontier function by fitting pieces of hyper planes to envelope an observed set of data formed by the inputs and outputs (Oum and Chunyan, 1994). Efficiency measures are obtained by estimating the distance of the observations relative to the enveloped surfaces. The main advantage of this technique in the estimation of technical efficiency is that it does not require prices neither for the outputs nor for the inputs. Moreover, this technique permits us to consider the multi-input and multi-output case. However, because DEA estimates a production frontier function using linear programming methods, this approach is deterministic, that is, it does not admit noise. Detailed discussions concerning DEA and its wide applications can be found in e.g. Ali and Seiford (1993), Banker et al., (1984), Bowlin (1998) and Seiford and Thrall (1990). One of the main disadvantages of the non-parametric approach is the absence of accommodation of random shocks or measurement errors in the estimation of efficiency. To estimate technical efficiency using a parametric approach, it is necessary to estimate the relationship between outputs and inputs using statistical techniques, that is, it requires the assumption of a particular functional form for the frontier function (e.g. production, cost function). In additional, an error term to account for technical inefficiency is included in the frontier function. There are a great variety of specifications of functional forms to estimate a particular frontier production function. They exist from the simple forms such as Cobb-Douglas up to the more complex structures such as the translog form (Coelli et al., 1998). Moreover, according to the assumptions of the efficiency term added to the frontier model, the parametric approach can be a deterministic model or stochastic models.

Stochastic frontier production function can be estimated using either the ML method or using a variant of the COLS method suggested by Richmond (1974). The COLS approach could be preferred because it is not as computational demanding as ML, which requires numerical solution of the likelihood. This distinction, however, has lessened over the past years with the availability of software such as the LIMDEP econometrics package (Greene, 1992) and the FRONTIER program (Coelli, 1992; 1994), both of which automate the ML method.

Several authors present strength and weaknesses of various techniques used in the efficiency measurement. For example, Coelli, (1995) among others noted that the stochastic frontier model specification not only addressed the noise problem associated with earlier (deterministic) frontiers, but also permitted the estimation of standard error and test of hypotheses which were not possible with the earlier deterministic models because of the violation of certain maximum likelihood regularity conditions. However, it was further noted that there is a problem of no a priori justification for the selection of any particular distributional form. Though the specification of a more general distributional forms such as the truncated-normal (Stevenson, 1980) and the two parameter gamma (Greene, 1990) has partially alleviated this problem but the resulting efficiency measure may still be sensitive to distributional assumption. The need for imposing an explicit parametric form for the underlying technology and an explicit distributional assumption for the inefficiency term are the main weaknesses of the parametric approach.

However, DEA is deterministic and attributes all deviations from the frontier to inefficiency; a frontier estimated by DEA is likely to be sensitive to measurement error or other noise in the data. Various authors have examined the empirical performances of these two approaches. For instance, Louisa, Sean and Simon, (1998) found out that overall distribution of the technical efficiency scores for the stochastic production frontier (SPF) and VRS DEA models were similar while the efficiency scores for individual boat varied considerably for these two approaches. Also, Sharma, Leung and Zaleski (1999) found the result from the DEA to be more robust than those from the parametric.The objective of this study is to analyze the technical efficiency of maize production using parametric and non-parametric methods.

METHODOLOGY

This study was carried out in Ogo-Oluwa Local Government Area of Oyo State. Ogo-Oluwa Local Government Area lies between latitude 6^{o}N and longitude 4^{o}E of the Greenwich Meridian with annual temperatures of 26.2^{o}C, mean annual rainfall of 1247mm. The main occupation of the inhabitants is farming. The types of crops cultivated in the study area are yams, cassava, groundnuts, maize, beans, pepper, soya beans and vegetables. Two-stage random sampling technique was used in collecting primary data. Firstly, five villages were randomly selected from the local government area. Secondly, sixteen (16) respondents (maize farmers) were randomly selected from each of the villages making a total
of eighty (80) respondents.

DEA is non parametric approach method which involves the use of linear programming to construct a piecewise linear envelopment frontier over the data points such that all observed points lie on or below the production frontier. Let X be a K * N matrix of inputs, which is constructed by placing the input vectors x_i, of all N firms side by side and Y denotes the M * N output matrix which is formed in analogous manner. The output oriented VRS DEA frontier is defined by the solution to N linear programs of fee for.

$$
\begin{aligned}
&\text{Min } \Phi \\
&\Phi, T \\
&\text{Subject to} \quad y_i/\Phi + YT > 0 \\
&\qquad\qquad\quad\; x_i + XT \geq 0 \\
&\qquad\qquad\quad\; N/T = 1 \\
&\qquad\qquad\quad\; T \geq 0
\end{aligned}
$$

Where NI is an N x I vector of Is, T is an N * I vector of weights and ? is the output distance measure. We have to note that 0 < < 1 and that 1/ is the proportional expansion in outputs that could be achieved by the i + e firm, with input quantities held constant. In a similar manner, the input - oriented VRS DEA frontier is defined by the solution to N linear programs of the farm.

Where is the input distance measure. Also note that $1 < \ell < \infty$ and that 1/ is the proportional reduction in inputs that could be achieved by the i+e firm, write output quantities held constant. The technical efficiency measure under CRS, also called the "overall" technical efficiency measure, is obtained by solving N linear programs of the form.

$$\text{Min } \Phi^{CRS}$$
$$\Phi_i^{CRS}$$

Subject to $\quad -YT + Y_i > 0$

$\Phi_i^{CRS} x_i - XT \geq 0$

$T > 0$

Where is a technical efficiency measure of the ite firm under CRS and $0 \underline{\alpha} \Phi_i^{CRS} \underline{\alpha} 1$.

The output and input oriented models will estimate exactly the same frontier surface and therefore, by definition, identify the same set of firms as being efficient. The efficiency measures may, however, differ between the input and output orientations. Under the assumption of CRS, the estimated frontier and the efficiency measures remain unaffected by the choice of orientation.

One output and five inputs were used in the models. The only output is the maize yield per hectare. The inputs are farm size, labour, seed, fertilizer and pesticide. The stochastic production frontier model used for analysis is of the form

$$Q_i = f(X_i;\beta)e^{\varepsilon} \text{ …………………… (1)}$$

Where

Q_i = output of ith farmer

X_i = vector of inputs

$\ln Q_i = \beta_o + \beta_1 \ln X_i + \beta_2 \ln X_2 \pm \beta_3 \ln X_3 + \beta_4 \ln X_4 + \beta_5 \ln X_5 + V - U$

β = vector of parameters to be estimated

e = error term

= a stochastic disturbance term consisting of two independent elements V and U.

Where: = V - U …………………. (2)

V is a symmetric random error that is assumed to account for measurement error and other factors not under the control of the farmer e.g. weather and luck (Thanda and Mathias, 1988) while U reflects the technical inefficiency i.e. what s left for the farmer to reach the outer bound production function or the frontier. To estimate , the stochastic production frontier model has to be linearised thus: In

....… (3)

X_1 = Farm size (Hectares)

X_2 = Total labour used in production (Man-days)

X_3 = Seed (kg)

X_4 = Fertilizer (kg)

X_5 = Pesticide (N)

The FRONTIER version 4.1 computer programme (Coelli, 1996) was used to estimate and also to predict the individual efficiency of the farmers.

RESULTS AND DISCUSSION

The summary statistics of variables for the production frontier estimation is presented on table 1. The table revealed that the output per hectare of maize is 613.06 kgha^{-1} with a standard deviation of 1687.11 kgha^{-1}. The large variability by the standard deviation implies that the farmer operated at different levels of farm size which tends to affect their output levels. The mean farm size was 4.17 ha with a standard deviation of 3.35 ha. The variability is due to changes in hectares of maize under the production seasons. As it is seen from table 1, large variations exist in all of the inputs. The greatest variation is in pesticide cost and fertilizer use. Such a great variation in input use levels may be an indication of a mismanagement problem.

Table 1: Summary Statistics for Variables Used.

Input/output variable	Mean	Standard Deviation	Min	Max
Output(kgha^{-1})	613.06	1687.11	4.11	13343.22
Farm size(ha)	4.17	3.35	0.20	20.24
Labour (man days ha^{-1})	39.79	61.61	2.13	259.95
Seed(kgha-1)	28.91	80.31	0.74	691.85
Fertilizer(kgha^{-1})	148.73	465.33	6.18	3706.45
Pesticide(#ha^{-1})	5397.20	9683.50	247.1	54361.00

Source: Field survey, 2010

The estimated parameters and related statistical test result obtained from the analysis are presented in Table 2. The signs of the entire coefficients except pesticides are positive and conform to a priori expectation. Three of the coefficients are found to be statistically significant. The significant coefficients are farm size, seed and fertilizer. This implies that as the use of each of these inputs increases, output increases. The gamma-value of 0.779 implies that 77.9 % of the variances in output among the farms are due to differences in technical efficiency.

Table 2: Coefficients of Stochastic Frontier Function

Variable	Coefficient	Standard error	t - value
Constant	1.011	1.128	0.897
Farm size	0.199	0.096	2.073**
Labour	0.374	0.244	1.533
Seed	0.161	0.071	2.268**
Fertilizer	0.245	0.148	1.650*
Pesticide	-0.195	0.129	-1.512
Sigma-squared	2.346	0.799	2.935***
Gamma	0.779	0.174	4.483***
Log-likelihood function	-100.69		
RTS 0.979			

Source: Data analysis, 2010

*** - estimates significant at 1% level; ** - estimates significant at 5% level; * - estimates significant at 10% level

Out of the 80 maize farms studied, 9 farms under CRS and 32 farms under VRS are fully efficient. 18 farms under CRS show a performance below 0.1. On the other hand, no farm was found to be fully efficient with SFA. The greatest efficiency score was found to be 0.829.The average overall technical efficiencies are 0.659, 0.326 and 0.829 for SFA, CRS and VRS respectively. Under the prevailing conditions, about 11% and 40% 0f farms wee identified as fully technically efficient under CRS and VRS specification respectively. The observed difference between CRS and VRS measures further indicated that some of the farmers did not operate at an efficient scale and improvement in the overall efficiencies could be achieved if the farmers adjusted their scales of operation. Efficiency scores given to each individual farm and mean efficiency were different between different models. This is expected to a certain extent since different models work under different assumption. Since DEA attributes any deviation from the frontier to inefficiencies, DEA efficiency scores are expected to be less than those obtained with SFA. This is true in this study. SFA gave higher scores than DEA. Sharma, Leung and Zaleski (1997) reported a contrary situation in their study where they investigated productive efficiency of the swine industry in Hawaii and compared results from parametric and non-parametric methods. The difference in efficiency scores between SFA and DEA may also be explained as follows. Farms appearing less efficient under SFA have a relatively large inefficiency component (U) of the error term compared to the random component (V).

Table 3: Distribution of Technical Efficiency Scores obtained by SFA and DEA Models.

Efficiency scores	SFA	CRS	VRS	SE
0.1	-	18(22.5)	-	4(5.0)
0.1-0.2	1(1.3)	25(31.3)	-	28(35.0)
0.21-0.3	1(1.3)	7(8.8)	-	1316.3)
0.31-0.4	-	7(8.8)	2(2.5)	7(8.8)
0.41-0.5	4(5.0)	5(6.3)	3(3.8)	5(6.3)
0.51-0.6	17(21.3)	5(6.3)	9(11.3)	4(5.0)
0.61-0.7	26(32.5)	-	7(8.8)	3(3.8)
0.71-0.8	24(30.0)	4(5.0)	9(11.3)	3(3.8)
0.81-0.9	7(8.8)	-	9(11.3)	3(3.8)
0.91-1.00	-	-	9(11.3)	1(1.3)
1.00	-	9(11.3)	32(40.0)	9(11.3)
Mean	0.659	0.326	0.829	0.384
Min	0.146	0.010	0.383	0.010
Max	0.822	1.000	1.000	1.000
S.D	0.120	0.301	0.193	0.314

Source: Data Analysis, 2010. *Figures in parentheses are percentages

Spearman correlation coefficients between the technical efficiency scores were computed and given in Table 4 in order to examine agreement between results obtained from DEA and SFA. All correlation coefficient are positive and significant at 0.01 Level except for TE - SFA and TE - VRS. This indicates a strong agreement between results. The strongest correlation is between stochastic frontier and DEA CRS models. This study to some extent is in line with the earlier findings by Alemdar and Oren (2006).

Table 4: Spearman Correlation Coefficient among alternative Efficiency Measures

	TE - DEA (CRS)	TE - DEA (VRS)	TE - SFA
TE - DEA (CRS)	1.000		
TE - DEA (VRS)	0.313*	1.000	
TE - SFA	0.756*	0.087	1.000

* means coefficients are significant at the 0.01 level (2 - tailed).

For the inefficient farms, the causes of inefficiency may be either inappropriate scale or misallocation of resources. Inappropriate scale suggests that the farm is not taking advantage of economies of scale, while misallocation of resources refers to inefficient input combinations. In this study, scale efficiencies are relatively low. Therefore, efficiencies are mainly due to misallocation of resources. Mean scale efficiency of the maize farm is 0.384 (table 2). Of the 80 maize farms, 10 show constant return to scale and 70 show increasing return to scale. This result shows that there is large scale inefficiency in the study area. This implies that most of the farm should be larger than their present size in order to achieve higher production given the available factor mix. The issue of large scale inefficiencies has been identified by earlier studies. Abay, Miran and Gunden (2004) reported large scale inefficiency for tobacco farmers in Turkey. On the other hand, Haji (2006) found that scale inefficiencies were nearly absent in more traditional farming systems. Table 5 shows that the mean farm size and mean output are 3.56 ha and 2125 kg ha^{-1} respectively for fully efficient farms. The mean output of optimal scale is larger than that of sub-optimal scale. The result indicates that the optimal output level overlap a substantial portion of sub-optimal. The scale properties given by SFA analysis can be observed by examining sum of values presented in table 2. Sum of coefficients is less than 1. This indicates that maize production in the study area follows the law of decreasing returns of scale.

Table 5: Characteristics of farms with respect to returns to scale

	No of Farms	Mean of Size (ha)	Mean Output (Kg ha-1)
Sub - Optimal	70	4.25	606.5
Optimal	10	3.56	2125
Super - Optimal	-		

Source: Field Survey, 2010.

On the table 6, the greatest input excess is seed used. Fertilizer cost and labour working man-days follow this. According to these results, sample farms could reduce seed use by 17% staying at the same production level. Number of farms using excess is also high 31. DEA analysis reports excess use for all inputs especially for seed used. SFA analysis shows a negative elasticity for pesticides only.

Table 6: Input slack and number of farms using excess inputs

Inputs	No of farms	Mean Slack	Mean input use	Excess-input use%
Farm Size	22	0.379	4.166	9.10
Lab	20	6.154	61.046	10.08
Seed	31	6.300	36.71	17.16
Fertilizer	18	34.85	207.5	16.80
pesticide	19	799.67	8346.6	9.58

Source: Field Survey, 2010.

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