<u>TECHNOLOGICAL INNOVATION AND EFFICIENCY IN THE NIGERIAN MAIZE SECTOR: PARAMETRIC STOCHASTIC AND NON-PARAMETRIC DISTANCE FUNCTION APPROACHES</u>

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TECHNOLOGICAL INNOVATION AND EFFICIENCY IN THE NIGERIAN MAIZE SECTOR: PARAMETRIC STOCHASTIC AND NON-PARAMETRIC DISTANCE FUNCTION APPROACHES

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Abstract

The current food crisis all over the globe has necessitated alternative policy actions by various stakeholders in almost all countries of the world. Consequently, efforts are focused on increased investment in agricultural research and development. The study evaluates impact of technological innovations on estimates of technical, allocative and cost efficiency from a parametric stochastic and non-parametric distance functions. Inefficiency effects are modelled in a second stage endogeniety-corrected Tobit regression model as a function of technological innovation and other policy variables. The results from both approaches show there is substantial technical, allocative and cost inefficiency in maize production and that analysis of technical, allocative and cost efficiency with respect to technological innovation and other policy factors are robust. Our results show that policies aimed at maize technology development and their timely dissemination, improvement in education, access to credit and extension among others could promote technical, allocative and cost efficiency, reduce yield variability, enhance farm income, food security and reduce poverty in Nigeria.

Key Words: technology, efficiency, maize, parametric, non-parametric, distance function, Nigeria

1. Introduction

The current global food crisis has raised concern among policy makers in various countries of the world. Increasing agricultural productivity is one of the major solutions to effectively addressing the food shortage problem that has fuelled increases in food prices all over the world. Subsequently, efforts are being channeled to ways in which increased productivity can be achieved. Maize has been identified as one of the most potential cereals grown globally, and is the third after wheat and rice in total food grain production. Due to its high adaptability and productivity, the cultivation of maize spread rapidly around the globe and currently it is being produced in most countries of the world (Anupama *et al*., 2005). In Nigeria, maize is one of the main staple crops and featured among the five food crops (cassava, maize, wheat, rice and sugar) whose production is to be promoted for attainment of food self-sufficiency as revealed by the Minister of Agriculture and Water Resources (Sayyadi, 2008). In Nigeria, maize production ranks third after sorghum and millet among the cereal crops (FAO, 2009). A survey conducted in Nigeria reveals that maize accounts for about 43 percent of calorie intake, with income elasticity of demand of 0.74, 0.65 and 0.71 for low income, high income and all sample households respectively and contributes to 7.7 percent of total cash income of farm households (Nweke et al. 2002; Nweke, 2006). Apart from been a food crop, maize has equally become a commercial crop on which many agro-based industries depend on as raw materials. Maize contributes about 80 percent of poultry feeds and this has great implication for protein intake in Nigeria (FAO, 2008). Maize is therefore considered as very vital to the economic growth of the nation through its contribution to food security and poverty alleviation.

Current maize production is about 8 million tonnes and average yield is 1.5 tonnes per hectare. The average yield is low when compared to world average of 4.3 tonnes/ha and to that from other African countries such as South Africa with 2.5 tonnes/ha (FAO 2009). Thus, there has been a growing gap between the demand for maize and its supply. The stronger force of demand for maize relative to supply is evidenced in frequent rise in price of maize in Nigeria. In view of the high level demand for maize in industries (flour mills, breweries, confectioneries etc), for human and animal consumption, the Federal Government under the leadership of President Olusegun Obasanjo in 2006 initiated a programme to double maize production in the country both for national consumption and international export through promotion of improved agricultural technologies such as fertilizer, hybrid seeds, pesticides, herbicides and better management practices. (USAID, 2006). Since then, several stakeholders have alleged their support for this program as every attempt to boost its production is expected to enhance food security, serve as import substitution and earn foreign exchange for the country through export to food deficit countries (IITA, 2007).

The development of technological innovations often come at a cost, thus ascertaining their feasibility in terms of impact on farm households is very crucial for policy analysis. This study focuses on impact on efficiency of farm households. Policy conclusions may vary depending on methodology used. However, consistency of different approaches validates policy conclusions. Two broad approaches are usually followed in efficiency analysis in the literatures; parametric and non-parametric approaches. The parametric approach could either be stochastic or deterministic. Whereas the stochastic frontiers accounts for noise in the data, the deterministic frontiers do not, rather all deviations of output from the frontier is attributed to inefficiency. Non-parametric approaches are mainly deterministic. Under the parametric approach, the production technology has basically been represented either by a production or cost function. The use of distance functions have recently begun. Data envelopment analysis (DEA) is the most commonly used non-parametric frontier approach. The major disadvantage of the DEA approach over its parametric counterpart is that it takes no account of possible influence of measurement error and other noise in the data. However, it has the advantage of removing the necessity to make arbitrary assumptions about the functional form of the frontier and the distributional assumption of the error terms. The parametric stochastic distance frontier (SDF) has advantages and disadvantages as well. The advantages include its ability to control for random unobserved heterogeneity among the firms. Second, by using SDF, the statistical significance of the variables determining efficiency can be verified using statistical tests. Disadvantages of the parametric stochastic approach consist of the need of assumptions about the production technology and distributional of the two error components.

Given the different strengths and weaknesses of the two approaches, this study wishes to shed more light on the sensitivity of technical (TE), allocative (AE) and cost (CE) efficiency estimates obtained from different approaches. Also some comparison of technological innovation impact on efficiency in the different approaches will be made. Specifically, we compare results from parametric stochastic input distance function (SIDF) with its non-parametric counterparts, DEA. This study is by no means the first to analyse the sensitivity of results to different approaches. Examples of comparative studies in agriculture involving distance functions include Arega and Manfred (2005), Herrero (2005), Arega *et al.* (2006). Similar studies in other sectors are Coelli and Perelman (1996, 1999, 2000), Cuesta *et al.* (2009). All of these studies compared only technical efficiency estimates from different approaches. However, we note that the modelling and estimation of both technical and allocative efficiency of agricultural production is often motivated by the need for a more complete representation of economic or cost efficiency of farmers implied by the economic theory of production. All the studies with exception of Herrero (2005) and Cuesta et al. (2009) compared results from deterministic distance functions with other approaches. We argue in this study that given the uncertainties surrounding agricultural production, the modelling of efficiency in a stochastic distance function framework is necessary. Based on these knowledge gaps, this study compares the performance of results from SIDF and DEA approaches by (i) assessing the technical, allocative and cost efficiency of maize farmers (ii) analysing the impact of technical innovation on these efficiency measures. To the best of our knowledge, there has been no study that analyses comprehensively the impact of technology on farm efficiency.

The remainder of the paper is organised as follows. In section 2 we present the analytical framework. In section 3 we present the empirical model. In section 4 we present data and variable description. In section 5 we compare results from SIDF and DEA models. Finally, conclusions are drawn in Section 6.

2. Analytical Framework

The production technology of a farm may be described using a distance function, which is a multi-input and multi-output technology. The notion of distance function was first introduced by Shepherd (1953). Whereas the output distance function looks at by how the output vector may be expanded with the input vector held fixed, the input distance functions looks at the proportional contraction of the input vector with the output vector held fixed. In most empirical studies, the selection of orientation is justified based on exogeneity/endogeniety argument for inputs and outputs. However, (Coelli, 1995, Coelli & Perelman, 1999) observed that in many instances, the choice of orientation will have only minor influences upon the efficiency scores obtained. Based on this, the study employs the input orientation and therefore the discussion is limited to input distance function. In this study we make comparison of parametric stochastic and non-parametric input distance functions.

2.1 Parametric stochastic input distance function (SIDF)

The input distance function may be defined on the input set, $L(y)$, as

$$D_I(x,y) = \max\{\rho : (x/\rho) \in L(y)\} \qquad (1)$$

where the input set $L(y)$ represents the set of all input vectors, $x \in R_+^K$, which can produce the output vector, $y \in R_+^M$. That is,

$$L(y) = \{\ x \in R_+^K :\ x \text{ can produce y}\} \qquad (2)$$

$D_I(x,y)$ is non-decreasing in x , linearly homogenous and concave in x, and non-increasing and quasi-concave in y (Coelli et al., 2005). The distance function, $D_I(x,y)$, will take a value which is greater than or equal to one if the input vector, x, is an element of the feasible input set, $L(y)$. That is, $D_I(x,y) \geq 1$ if $x \in L(y)$. Furthermore, the distance function will take a value of unity if x is located on the inner boundary of the input set.

The value of the distance function is not observed so that imposition of a functional form for $D_I(x,y)$ does not permit its direct estimation. A convenient way of handling this problem was suggested by Lovell et al. (1994) who exploit the property of linear homogeneity of the input distance function, expressed mathematically as:

$$D_I(\lambda x, y) = \lambda D_I(\mathbf{x}, y) \;\forall \lambda > 0 \qquad (3)$$

Assuming we have access to cross-sectional data on N firms, producing M outputs using K inputs. If we set $\lambda = 1/x_1$ and if we choose a Cobb-Douglas functional form, then equation (3) can be expressed as:

$$-\ln x_{Ki} = \beta_0 + \sum_{k=1}^{K-1} \beta_k \ln(x_{ki}/x_{Ki}) + \sum_{m=1}^{M} \alpha_m \ln y_{mi} - \ln(D_I)\,; \qquad i = 1,2...N \qquad (4)$$

where distance function, $-\ln(D_I)$ measures the deviation of an observation (x, y) from the deterministic border of the input requirement set $L(y)$ which, following the stochastic frontier literature, is itself explained by two components, equation (4) can be rewritten to obtain estimable equation in a stochastic frontier framework:

$$-\ln x_{Ki} = \beta_0 + \sum_{k=1}^{K-1} \beta_k \ln(x_{ki}/x_{Ki}) + \sum_{m=1}^{M} \alpha_m \ln y_{mi} + v_i - u_i\,; \qquad i = 1,2...N \qquad (5)$$

The random errors, v_i are assumed to be independently and identically distributed as $N(0, \sigma^2{}_v)$ random variables and independent of the u_i's , which are assumed to either be a half-normal distribution i.e., $\left| N(0, \sigma_u{}^2) \right|$ or exponential distribution i.e. EXP $(\mu, \sigma_u{}^2)$ or truncated normal (($N(\mu, \sigma_u{}^2)$) or gamma distributions. The predicted radial input-oriented measure of TE for a unit of analysis is given as:

$$T\hat{E}_i = 1/\hat{D}_I = E[\exp(u_i) | v_i - u_i] \qquad (6)$$

Using the properties of the input distance function, the duality between the cost and input distance function can easily be expressed as:

$$C(w, y) = \underset{x}{M}\{wx : D_I(x, y) \geq 1\} \qquad (7)$$

where C is the cost of production and w denotes a vector of input prices.

Using the first order condition for cost minimization and by making use of Shephard's Lemma, it is possible to calculate AE and CE.

2.2 Non-parametric distance functions (DEA)

DEA is a non-parametric approach to distance function estimation (Fare et al, 1994). The purpose of the approach is to construct a non-parametric envelopment frontier over the data points such that all observed points lie on or below the production frontier. In this study, both variable returns to scale (VRS) and constant returns to scale (CRS) DEA models are considered. The DEA model could have either an input-orientation or an output-orientation just like its parametric counterpart. However, for appropriate comparison with the parametric approach given the reason stated in the previous section, the discussion is focused on the input-orientated DEA model.

Assuming there is data on K inputs and M outputs on each of N firms. For i-th firm, these are represented by the vectors x_i and y_i respectively. The K x N input matrix, X and the M x N output matrix, Y, represent the data of all N firms. The purpose of the approach is to construct a non-parametric envelopment frontier over the data points such that all observed points lie on or below the production frontier.

The input-oriented constant returns to scale DEA frontier is defined by the solution to N linear programs of the form:

$$\min_{\theta,\lambda} \theta,$$

$$\begin{aligned} \text{subject to } \; & -y_i + Y\lambda \geq 0, \\ & \theta x_i - X\lambda \geq 0, \\ & \lambda \geq 0 \end{aligned} \qquad (8)$$

where θ is the input distance measure and λ is a Nx1 vector of constants. The value of θ obtained is the efficiency score for the i-th firm and will satisfy $0 \leq \theta \leq 1$, with value of 1 indicating a point on the frontier and hence a technically efficient firm. Inefficient units can be transformed into efficient ones by radially contracting its inputs by multiplying them by θ.

The CRS linear programming problem can easily be modified to account for variable returns to scale by adding the convexity constraint: $N1'\lambda = 1$ to equation (8) to provide an input-oriented VRS model.

With availability of price information, behavioural objectives can be considered, such as cost minimisation or revenue maximisation so that both technical and allocative efficiencies can be measured. For the case of a CRS cost minimisation, one would run the input-oriented DEA model set out in equation (8) to obtain TE. One would then run the following cost minimisation DEA

$$\min_{\lambda, x_i *} \; w_i' x_i *,$$

$$\begin{aligned} \text{subject to } & -y_i + Y\lambda \geq 0, \\ & x_i * - X\lambda \geq 0, \qquad (9) \\ & \lambda \geq 0 \end{aligned}$$

where w_i is a vector of input prices for the i-th firm and $x_i *$ is the cost minimising vector of input quantities for the i-th firm given the input prices w_i and the output levels y_i and this is calculated by the model. The total CE of the i-th firm would be calculated as

$$CE = \frac{w_i' x_i *}{w_i' x_i} \qquad (10)$$

Allocative efficiency is calculated as

$$AE = \frac{CE}{TE} \qquad (11)$$

For a VRS cost-minimisation, equation (9) is altered by adding the convexity constraint, $N1'\lambda = 1$.

3. Empirical Models

Under the parametric approach, a Cobb-Douglas stochastic input distance function is assumed for this study. Although Klein (1953) noted that the Cobb-Douglas function imposes a functional form that is convex to the origin in the output dimensions, which is hence not consistent with profit maximisation, we argue in line with Coelli et al. (2003), that it is not a problem when there is only one output variable (as in our study). Even if there is more than one output variable, one could argue that the Cobb-Douglas provides a first-order approximation to the slope of the production possibility surface at the mean of the data.

Hence, if one is focussing on cost minimisation issues, and not profit maximisation, the model should still provide a reasonable approximation to the underlying technology, especially in small samples where degrees of freedom are limited.

For the case of single output, K inputs, N farms, the empirical model is specified as:

$$\ln D_i = \delta + \alpha \ln Y_i + \sum_{j=1}^{4} \beta_j \ln X_{ji}, \;\; i = 1,...N, \tag{12}$$

where Y_i is the observed maize output for the i-th farmer and X_{ji} = is the j-th input quantity for the i-th farmer, namely land, labour, inorganic fertilizer and index of other inputs such as seed, pesticide and herbicides. In represents a natural logarithm, and δ, α and β_j are unknown parameters to be estimated.

Imposing the restriction for homogeneity of degree +1 in inputs upon equation (12),

$$\sum_{j=1}^{4} \beta_j = 1, \tag{13}$$

We obtain:

$$-\ln X_{ki} = \delta + \alpha \ln Y_i + \sum_{j=1}^{4-1} \beta_j \ln\left(X_{ji} / X_{ki}\right) - \ln D_i, \tag{14}$$

The unobservable distance term "$-\ln \mathrm{D_i}$" represents a random term and can be interpreted as the traditional stochastic frontier analysis (SFA) disturbance term, ε_i. Thus equation (14) can be rewritten as:

$$-\ln X_{ki} = \delta + \alpha \ln Y_i + \sum_{j=1}^{4-1} \beta_j \ln\left(X_{ji} / X_{ki}\right) + v_i - u_i, \tag{15}$$

The statistical noise (v_i) are assumed to be iid $N(0, \sigma_v{}^2)$ and independent of u_i, where u_i is independently distributed. u_i is assumed to have a half-normal distribution $\left|N(0, \sigma_v{}^2)\right|$ in this study given that a preliminary test rejected the alternative of truncated normal distribution at 5% level of significance.

The input-orientated TE scores are predicted using the conditional expectation predictor:

$$T\hat{E}_i = E[\exp(-u_i) | \varepsilon_i)], \tag{16}$$

From the parameters of the Cobb-Douglas input distance function, the corresponding parameters of the dual cost function is analytically derived and is defined as:

$$\ln C_i = b_0 + \sum_{j=1}^{4} b_j \ln W_{ji} + \phi \ln Y_i \qquad (17)$$

where C_i is the cost of production of maize for the i-th farmer, W_{ji} is the j-th input price which includes the price of land, price of labour, price of inorganic fertilizer and price index for other inputs. b_0, b_j and ϕ are unknown parameters which are derived from the primal function. Using the first order condition for cost minimization, it can be shown that the parameters of the cost and input distance function are related as follows:

The technically efficient input quantities are predicted as follows:

$$\hat{X}_{ji}^{T} = X_{ji} \times T\hat{E}_i , \qquad \text{j = 1, 2, 3, 4} \qquad (18)$$

The cost-efficient input quantities are predicted by making use of Shephard's Lemma, which states that they will equal the first partial derivatives of the cost function:

$$\hat{X}_{ji}^{C} = \frac{\partial C_i}{\partial W_{ji}} = \frac{\hat{C}_i b_j}{W_{ji}}, \quad \text{j=1,2,3,4} \qquad (19)$$

where $\hat{C}_i$ is the cost prediction obtained by substituting the estimated parameters into (the exponent) of equation (17). Thus, for a given level of output, the minimum cost of production is $\hat{X}_i^C \cdot W_i$, while the observed cost of production of the i-th farmer is $X_i \cdot W_i$. These two cost measures are then used to calculate the CE scores for the i-th farmer:

$$C\hat{E}_i = \frac{\hat{X}_i^C \cdot W_i}{X_i \cdot W_i}, \qquad (20)$$

AE is calculated residually as:

$$A\hat{E}_i = \frac{C\hat{E}_i}{T\hat{E}_i}, \qquad (21)$$

Each of these three efficiency measures takes a value between zero and one, with a value of one, indicating full efficiency.

Under the non-parametric approach, the CRS and VRS DEA and CRS and VRS cost minimising DEA models as presented in section 2.2 are estimated for the same number of farm households, same output variable and same input variables as for the SIDF.

To analyse the impact of technological innovation (hybrid seed, inorganic fertilizer, herbicides and conservation practices) and other policy variables on efficiency, a second stage procedure is used whereby the efficiency scores are regressed on the selected explanatory variables using a two-limit Tobit model since efficiency scores are bounded between 0 and 1. The Tobit model is specified as:

$$\left. Y_i^* = \beta_0 + \sum_{\substack{n=1\\=0}}^{10} \beta_n X_{in} + \sum_{\substack{m=1\\=0}}^{4} \beta_m T_{im} + u_i \text{ if } L_i < \beta_0 + \sum_{\substack{n=1\\=0}}^{10} \beta_n X_{in} + \sum_{\substack{m=1\\=0}}^{4} \beta_m T_{im} + u_i < U_i \right\} \quad (22)$$

where Y_i^* is a latent variable representing the efficiency measure for each farm household, X_i is a $nx1$ vector of explanatory variable for the *i*th farm, T_i is an $mx1$ vector of technology variables for the *i*th farm, β_n and β_m is a $kx1$ and $mx1$ vectors of unknown parameters to be estimated, u_i are residuals that are independently and normally distributed, with mean zero and a constant variance σ^2, and L_i and U_i are the distribution's lower and upper censoring points, respectively. Denoting Y_i as the observed dependent variable, $Y_i = 0$ if $Y_i^* \leq 0$; $Y_i = Y_i^*$ if $0 < Y_i^* < 1$; and $Y_i = 1$ if $Y_i^* \geq 1$.

The inclusion of technology adoption variables in an efficiency model presents the problem of potential endogeneity and self selectivity. The exogeneity of these variables were tested using the instrumental variable approach as proposed by Smith and Blundell (1986). To correct for endogeneity, this study follows a two step approach, in which each endogenous technology variable is estimated in a first stage and their predicted values are included in a second step as additional explanatory variables which yields unbiased estimates of impact of technological innovation on efficiency.

4. Data and Variables

A multistage stratified sampling procedure was employed in selecting the respondents in this study. A total of 240 farmers were interviewed from four local government area of Benue State. Data on output and input quantities and prices were collected. One output variable (PROD) and four input variables (LAND, LABOUR, FERT and OTHER) were used in estimating the parametric stochastic input distance function. The output variable is the quantity of maize produced during 2008/2009 agricultural season by a farm household and is measured in kilograms. LAND is measured as the area of land in hectares cultivated with maize by a farm household in the relevant period. LABOUR is measured as the amount of both family and hired labour in mandays used by the farm household. FERT is the amount of inorganic fertilizer in kilograms used by the farm household. OTHER is the Fisher quantity index of seed, herbicides and pesticides used by the farm household. Observed average price per unit of inputs used were used in the analysis. W_{LAND} is rental price of a hectare of farm land. W_{LABOUR} is price of labour per day. W_{FERT} is price of inorganic fertilizer per kilogram. W_{OTHER} is an implicit price index of seed, herbicides and pesticides derived by dividing the cost of other inputs by OTHER. All prices were in local currency, Naira.

Four variables indexing technological innovation included in second stage regression are HYV (area of maize farm cultivated with hybrid seed variety); FERT (area of maize farm applied with inorganic fertilizer); HERB (area of maize farm subjected to herbicide application); and PRACTICES (the number of conservation practices adopted by a farmer on his or her maize farm. Other variables include AGE (age of the household head in years); GENDER (dummy variable equal 1 if male or zero otherwise); EDU (number of years of formal education completed by the household head); HHS (number of persons in the household); OFFWORK (dummy variable equal to 1 for engagement in off-farm work); MFG (a dummy variable equal 1 if the household head is a member of any farmer organization); EXT (number of extension visits during the cropping period); CREDIT (a dummy variable equal 1 if farmer had access to credit); MARKET (distance to the nearest market).

Data was also collected on the instruments for the first stage of endogeneity-corrected Tobit model. For hybrid seed, YIELD is equal 1 if a farmer perceives that HYV produces more than the traditional variety. PALATABILITY is 1 if farmer perceive that HYV is more palatable than the local maize variety. For inorganic fertilizer, AVAILABILITY is equal 1 if farmer perceives that inorganic fertilizer is readily available. RAINRISK is equal 1 if farmer's perception of poor rainfall years is low. For herbicides, NEED is equal 1 if farmer perceives a need for weed control in his maize farm. ENVTRISK is 1 if farmer's perception of environmental effects of herbicide use is low. For conservation practices, SLOPE is equal 1 if the farmers maize farm is on a non-flat plane. DEGRADATION is 1 if farmer perceives soil erosion as a problem in his or her farm.

5. Estimation Results.

5.1 MLE Estimates of the Parametric Stochastic Input Distance Function

Table 1 presents the both the maximum likelihood (ML) and the ordinary least square (OLS) estimates of the parametric stochastic input distance function (SIDF) using the computer program, FRONTIER v. 4.1 developed by Coelli et al. (1996). Result shows that all variables are significant at 1% and have expected signs. The estimated coefficient of output is less than one in absolute terms indicating increasing returns to scale which for the parametric stochastic input distance function is computed as the inverse of the negative of this value, which is 1.351. The elasticity of the distance function with respect to a specific output is that it corresponds to the negative of the cost elasticity of that particular output. The elasticity of maize output being negative and highly significant implies that increasing production of maize results in a substantial increase in cost. The cost elasticity of 0.74, therefore, implies that a 10% increase in maize output results in a 7.4% increase in total cost. The elasticities of the distance function with respect to input quantities are equal to the cost shares and therefore reflect the relative importance of the inputs in the production process. For e.g. the elasticity with respect to land is largest with a value of 0.67 that means that the cost of that input represents 67% of total cost at the sample mean.

Table 1: The MLE and OLS estimates of the parametric SIDF

Variable	Mean	Parameter	OLS estimates	ML estimates
INTERCEPT		δ	3.718*** (0.200)	3.883*** (0.216)
PROD	1320.38	α	-0.729*** (0.021)	-0.740*** (0.021)
LAND	1.208	β_1	0.679*** (0.022)	0.667*** (0.024)
LAB	111.195	β_2	0.219*** (0.021)	0.233*** (0.023)
FERT	115.185	β_3	0.036***	0.038*** (0.003)
OTHER	56.343	β_4	0.067[a]	0.061
SIGMA-SQUARED		$\sigma^2 = \sigma_u^2 + \sigma_v^2$		0.043*** (0.006)
GAMMA		$\gamma = \sigma_u^2 / \sigma^2$		0.825*** (0.060)
LLF			125.479	132.274

***Significant at 1% level. Standard errors are shown in parenthesis.

[a] The estimate of β_4 is computed by the homogeneity condition

The estimate of the variance parameter, γ, is 0.83 and significant at 1% implying that 83% of the total variation in output is due to inefficiency. This result is confirmed by conducting a likelihood ratio test to test the hypothesis of OLS model versus frontier model. LR test statistic is 13.23 and this was significant when compared with mixed chi-square value of 5.412 at one degree of freedom, thus rejecting the adequacy of the OLS model in representing the data.

Based on the estimated parameters of the input distance function, the parameters of the corresponding dual cost function were derived and this formed the basis of computing the CE and AE. The dual cost frontier is given as:

$$\begin{aligned} \ln C_i &= -2.977 + 0.667 \ln W_{Land} + 0.233 \ln W_{Labour} + 0.038 W_{Fert} \\ &+ 0.061 \ln W_{Other} + 0.740 \ln PROD_i \end{aligned} \qquad (19)$$

where C is the cost of production for the ith farmer. W_{Land} is the rental price of land per hectare estimated at ₦4989.17 . W_{Labour} the price of labour per day estimated at ₦ 89.81. W_{Fert} is the price of inorganic NPK fertilizer per kg estimated at. ₦57.9. W_{Other} is implicit price index of other inputs estimated at ₦68.64 per kg.

5.2 Comparison of Efficiency Scores and Distribution

The frequency distribution of technical, allocative and cost efficiency from SIDF and DEA models on the entire sample are presented in table 2. The average technical efficiency is 86.7, 85.5 and 80.1 percent for SIDF, VRS DEA and CRS DEA respectively. This implies that for the SIDF, VRS DEA and CRS DEA, a cost saving of 13.3, 14.5 and 19.9 percent respectively could be achieved by improving technical efficiency without reducing outputs. The average allocative efficiency is 57.8, 73.8 and 65.9 percent for SIDF, VRS DEA and CRS DEA respectively. This implies that for the SIDF, VRS DEA and CRS DEA, a cost saving of 42.2, 26.2 and 33.1 percent respectively could be achieved by improving allocative efficiency without reducing outputs. The average cost efficiency is 50.2, 62.3 and 51.6 percent for SIDF, VRS DEA and CRS DEA respectively. This implies that for the SIDF, VRS DEA and CRS DEA, a cost saving of 49.1, 37.7 and 48.4 percent respectively could be achieved by improving cost efficiency without reducing outputs.

Table 2: Frequency distribution and estimates of efficiency

Efficiency index (%)	SIDF			DEA VRS			DEA CRS		
	TE	**AE**	**CE**	**TE**	**AE**	**CE**	**TE**	**AE**	**CE**
≤ 40	0	21	55	0	13	21	1	28	68
41-50	0	37	59	0	11	34	20	37	57
51-60	0	68	73	11	24	46	7	28	37
61-70	14	84	44	22	45	72	42	34	58
71-80	29	28	8	58	50	46	49	46	12
81-90	111	2	1	51	60	16	49	49	5
91-100	86	0	0	98	37	5	72	18	3
Mean	86.7	57.8	50.3	85.5	73.8	62.3	80.1	65.9	51.6
Min	64.3	23.0	19.6	51.5	28.8	28.8	37.5	22.4	14.9
Max	97.1	88.8	85.9	100.0	100.0	100.0	100.0	100.0	100.0
SD	7.6	11.9	12.0	12.9	16.7	14.6	15.8	19.2	15.6
Skewness	-1.2	-0.5	-0.2	-0.5	-0.7	-0.1	-0.4	-0.3	0.3
Kurtosis	3.9	2.8	2.7	2.4	3.0	2.9	2.4	2.0	2.8
CV	8.8	20.5	23.9	15.1	22.6	23.4	19.7	29.1	30.2

Min = Minimum; Max = Maximum; SD = Standard deviation; CV = coefficient of variation

To summarise, we observe that the SIDF produced higher technical efficiency values than the two DEA models. Similar results were obtained by Herrero (2005) and Cuesta et al. (2009) VRS DEA and CRS DEA produced higher allocative and cost efficiency values than the SIDF model. We do not have a previous study comparing AE and CE from parametric and non-parametric distance functions. The VRS DEA and CRS DEA exhibit greater variability than the SIDF efficiency measures. Maize farmers in Benue State operate with considerable inefficiency dominated by cost inefficiency as depicted by all approaches.

From table 2, it appears the means and distributions of efficiency scores from the different approaches are quite different. A formal test was conducted to evaluate the statistical significance of the difference between the parametric SIDF and nonparametric DEA technical, allocative and cost efficiency scores. This is achieved by testing different complementary hypotheses relative to: i) the equality of means (t-test), ii) the equality of distributions (Wilcoxon signed rank-test), and iii) the independence of the results with regard to their rank (Spearman's correlation test). Table 3 presents the results concluding that in the case of the t-tests, the differences between the SIDF and each of the DEA efficiency scores are statistically significant with a confidence of 95%. The Wilcoxon test further reinforces this result by indicating that the distributions within the bilateral pairs of results are also statistically different.

Table 3: Tests of hypothesis between efficiency scores from SIDF and DEA

Test	t-test[a] t-statistic			Wilcoxon test[b] Z-statistic			Spearman test[c] Spearman's ρ		
	TE	**AE**	**CE**	**TE**	**AE**	**CE**	**TE**	**AE**	**CE**
SIDF vs	2.133	-31.406	-39.925	2.936	-13.386	-13.431	0.705	0.872	0.963
DEA VRS	(0.034)	(0.000)	(0.000)	(0.003)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
SIDF vs	8.606	-13.045	-3.044	7.900	-9.842	-2.356	0.654	0.902	0.927
DEA CRS	(0.000)	(0.000	(0.003)	(0.000)	(0.000)	(0.019)	(0.000)	(0.000)	(0.000)

[a] H0 is the equality of means; [b] H0 is that both distributions are the same; [c] H0 is that both variables are independent; p-values are in parenthesis

To assess the overall consistency of the three methods in ranking individual farms in terms of efficiency, the coefficient of Spearman rank-order correlation has been calculated between the three models. Spearman's correlation suggests that the different farm household rank similarly when they are ordered according to either their parametric and nonparametric efficiency scores. These findings are consistent with that of Cuesta *et al.* (2009).

5.3 Comparison of policy impacts on efficiency estimates of SIDF and DEA models

Summary results for the exogeneity test the technological innovation variables are presented in the table 4. We observe that exogeneity of each variable in each model was rejected in at least one case. An endogeneity-corrected Tobit model is employed in the second step regression in the case of rejection of the null hypothesis.

Table 4: Summary result of Smith-Blundel test of exogeneity

Model	Predicted Residuals			
	RES_HYV	**RES_FERT**	**RES_HERB**	**RES_PRACTICES**
SIDF:				
TE	0.023** (0.012)	-0.025 (0.016)	-0.016 (0.014)	-0.005** (0.002)
AE	-0.113*** (0.024)	-0.056* (0.033)	-0.041 (0.029)	-0.002 (0.011)
CE	-0.088*** (0.022)	-0.088*** (0.022)	-0.050* (0.027)	-0.004 (0.010)
DEA VRS:				
TE	0.160*** (0.041)	0.003 (0.052)	0.092* (0.049)	0.012 (0.016)
AE	-0.140***(0.041)	-0.027 (0.054)	-0.030 (0.048)	-0.003 (0.017)
CE	-0.043 (0.029)	-0.025 (0.038)	-.009 (0.034)	-0.002 (012)
DEA CRS:				
TE	0.236*** (0.049)	-0.002 (0 .060)	0.045 (0.057)	0.012 (0.019)
AE	-0.198*** (0.041)	-0.043 (0.055)	-0.055 (0.050)	-0.008 (0.018)
CE	-0.063*** (0.024)	-0.058** (0.029)	-0.058** (.027)	-0.008 (0.010)

*****Significant at 1% level; **significant at 5% level; *significant at 10% level. Standard errors are shown in parenthesis.

The results of the second stage endogeneity-corrected Tobit model are presented in tables 5, 6 and 7. The significance of the likelihood ratio (LR) test in each model implies the joint significance of all variables included in the model. Thus, the hypothesis that the technology and other policy variables included in each model have no significant impact on efficiency is rejected. AGE has a positive and significant impact on technical efficiency in all three models but has positive and significant impact on cost efficiency VRS DEA models. Thus, the variable indexes experience and serve as a proxy for human capital showing that farmers with greater farming experience will have better management skills and thus higher efficiency than younger farmers. This result is consistent with the findings of Khai *et al.* (2008).

Table 5: Endogeneity-corrected Tobit results of determinants of technical efficiency

	SIDF	VRS DEA	CRS DEA	
Variable	Coeff.	Coeff.	Coeff.	Mean
GENDER	-0.013 (0.009)	-0.037 (0.030)	-0.044 (0.034)	0.888
AGE	0.002*** (0.000)	0.004*** (0.001)	0.004*** (0.001)	47.167
EDU	0.002*** (0.000)	0.004** (0.001)	0.004*** (0.002)	8.433
HHS	0.001*** (0.000)	0.000 (0.001)	0.003* (0.001)	11.742
LAND	-0.034*** (0.008)	0.071** (0.029)	0.152*** (0.034)	1.208
OFFWORK	-0.010* (0.006)	-0.037* (0.020)	-0.025 (0.023)	0.675
MFG	0.045*** (0.010)	0.059* (0.033)	0.111*** (0.037)	0.454
EXT	-0.003** (0.002)	0.002 (0.006)	-0.005 (0.006)	2.546
CREDIT	0.023*** (0.008)	0.044 (0.028)	0.025 (0.032)	0.138
MARKET	-0.000 (0.000)	-0.003* (0.002)	-0.002 (0.002)	6.278
HYV	0.011** (0.006)	0.024 (0.020)	0.038* (0.022)	0.895
FERT	0.018** (0.009)	0.029 (0.029)	0.027 (0.035)	0.816
HERB	0.008 (0.006)	0.000 (0.014)	0.054** (0.025)	0.591
PRACTICES	0.009*** (0.002)	0.024*** (0.007)	0.018** (0.008)	1.75
INTERCEPT	0.750*** (0.019)	0.592*** (0.065)	0.400*** (0.074)	
LLF	417.474	38.538	32.413	
LR TEST	293.72***	104.400***	106.510***	

*****Significant at 1% level; **significant at 5% level; ***significant at 10% level. Standard errors are shown in parenthesis. M.E. =Marginal effect

The estimated coefficient of the second human capital variable, EDU, from all three models was consistently positive though had significant impact on technical efficiency only. Similar positive and significant impact of education on technical efficiency of maize farmers in Nigeria was found by Oyewo and Fabiyi (2008). HHS was found to be positively and significantly related to technical and cost efficiency in the SIDF and CRS DEA models. A possible reason for this result might be that a larger household size guarantees availability of family labour for farm operations to be accomplished in time.

Table 6: Endogeneity-corrected Tobit results of determinants of allocative efficiency

	SIDF	VRS DEA	CRS DEA	
Variable	Coeff.	Coeff.	Coeff.	Mean
GENDER	0.012 (0.019)	0.011 (0.032)	0.019 (0.032)	0.888
AGE	-0.000 (0.001)	0.001 (0.001)	-0.002 (0.001)	47.167
EDU	0.000 (0.001)	0.001 (0.002)	0.002 (0.002)	8.433
HHS	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	11.742
LAND	0.045** (0.020)	-0.003 (0.030)	0.072** (0.030)	1.208
OFFWORK	-0.005 (0.013)	-0.003 (0.021)	-0.002 (0.021)	0.675
MFG	0.002 (0.021)	0.019 (0.035)	0.041 (0.035)	0.454
EXT	0.007* (0.004)	0.007 (0.006)	0.009 (0.006)	2.546
CREDIT	0.129*** (0.018)	0.170*** (0.029)	0.176*** (0.029)	0.138
MARKET	-0.000 (0.001)	-0.001 (0.002)	-0.001 (0.002)	6.278
HYV	0.034*** (0.013)	0.046** (0.021)	0.063*** (0.021)	0.895
FERT	0.057** (0.027)	0.078** (0.032)	0.107*** (0.032)	0.816
HERB	-0.014 (0.013)	-0.030 (0.023)	-0.031 (0.022)	0.591
PRACTICES	0.002 (0.005)	0.002 (0.008)	0.002 (0.008)	1.75
INTERCEPT	0.431*** (0.041)	0.689*** (0.068)	0.501*** (0.069)	
LLF	234.686	112.307	113.035	
LR TEST	139.09***	66.090***	122.850***	

*******Significant at 1% level; **significant at 5% level; *****significant at 10% level. Standard errors are shown in parenthesis. M.E. =Marginal effect

In this study, we observe that the relationship between LAND and the three efficiency measures in all the three models are inconsistent. Whereas, it has negative and significant impact on technical efficiency in the SIDF model, it has positive and significant impact on technical and cost efficiency in VRS DEA and positive and significant impact on all three efficiency measures in CRS DEA model. A similar contrasting result was found by Coelli et al. (2002) for modern boro rice farmers in Bangladesh, India. OFFWORK was consistently negative but has significant impact on technical efficiency only in both SIDF and VRS DEA models. This implies that farmers who engage in off-farm work are likely to be less efficient in farming as they share their time between farming and other income-generating activities. Productivity suffers when any part of production is neglected. This finding is consistent with that of Mariano et al. (2010).

Table 7: Endogeneity-corrected Tobit results of determinants of cost efficiency

	SIDF	VRS DEA	CRS DEA	
Variable	Coeff.	Coeff.	Coeff.	Mean
	0.000	-0.010	-0.007	
GENDER	(0.017)	(0.022)	(0.017)	0.888
	0.001	0.001**	0.001	
AGE	(0.001)	(0.001)	(0.001)	47.167
	0.001	0.001	0.001	
EDU	(0.001)	(0.001)	(0.001)	8.433
	0.001*	0.001	0.002***	
HHS	(0.001)	(0.001)	(0.001)	11.742
	0.025	0.036*	0.123***	
LAND	(0.018)	(0.021)	(0.018)	1.208
	-0.009	-0.018	-0.012	
OFFWORK	(0.012)	(0.015)	(0.012)	0.675
	0.028	0.027	0.039***	
MFG	(0.019)	(0.025)	(0.019)	0.454
	0.004	0.007*	0.002	
EXT	(0.003)	(0.004)	(0.003)	2.546
	0.130***	0.177***	0.131***	
CREDIT	(0.016)	(0.021)	(0.016)	0.138
	-0.000	0.001	-0.001	
MARKET	(0.001)	(0.001)	(0.001)	6.278
	0.035***	0.018	0.035***	
HYV	(0.011)	(0.014)	(0.011)	0.895
	0.060***	0.053**	0.091***	
FERT	(0.024)	(0.023)	(0.024)	0.816
	-0.005	-0.019	0.008	
HERB	(0.008)	(0.016)	(0.008)	0.591
	0.006	0.010*	0.007*	
PRACTICES	(0.004)	(0.005)	(0.004)	1.75
	0.305***	0.388***	0.163***	
INTERCEPT	(0.038)	(0.047)	(0.038)	
LLF	259.949	194.421	258.991	
LR TEST	196.07***	168.110***	318.070***	

*****Significant at 1% level; **significant at 5% level; *****significant at 10% level. Standard errors are shown in parenthesis. M.E. =Marginal effect

Membership in a farmer group (MFG) which indexes social capital affords the farmers opportunity of sharing information on modern maize practices by interacting with others as well as provides farmers with bargaining power in the input, output and credit markets. As expected, MFG was found to be consistently positive but has significant impact on TE in all three models and on CE in CRS DEA model only. The impact on TE is consistent with the findings of Ogunyinka and Ajibefun (2004).

The extension variable, EXT, presents a little puzzle. It is expected to be positive as it enhances farmers' access to information and improved technological packages. Whereas it to has negative and significant impact on TE in the SIDF model, it has positive and significant impact on AE and CE in the SIDF and VRS DEA models respectively. Some researchers (Okoye *et al.* 2006, Ogunyinka and Ajibefun, 2004) in Nigeria have found similar negative sign of the extension variable for technical efficiency. CREDIT is consistently positive and has significant impact on AE and CE in all three models but significant on TE in the SIDF model only. The availability of credit loses the production constraints thus facilitating timely purchase of inputs and therefore increasing productivity via efficiency. The result is consistent with the findings of Muhammad (2009).The variable MARKET serves as a proxy for the development of road and market infrastructures. It is generally believed that farms located closer to the market are more technically, allocatively and economically less inefficient than the farms located farther from the market as this might not only increase production cost but also affect farming operations, especially the timing of input application. This expectation was satisfied in this study as the MARKET variable was correctly signed in all three models though is significant in the SIDF model for TE only. GENDER was never significant in all cases.

Finally, an important goal of this study is to evaluate explicitly the impact of technological innovation on efficiency of maize farmers. Results show that HYV has positive and significant impact on TE, AE and CE in the SIDF and CRS DEA models but significant in the VRS DEA model for AE only. Zavale et al. (2006) and Chirwa (2007) obtained similar impact on TE and CE using production and cost frontier approaches respectively. These findings further strengthen the need for hybrid seed improvement and diffusion in Nigeria in line with the current doubling of maize production programme of the Federal Government.

FERT was also found to have positive and significant impact on AE and CE in all the three models but significant impact on TE in the SIDF model only. The findings are consistent with that of Okoye *et al.* (2006) and Msuya *et al.* (2008) who found a positive impact of inorganic fertilizer on allocative and technical efficiency respectively. The fertilizer technology can be said to corroborate to credit. Thus, failure to use fertilizer may result in irretrievable output loss. The variable, HERB, has positive and significant impact on TE in the SIDF model. In most cases it has negative though not significant impact on AE and CE in all three models. It could be that due to the farmers' perception of the health and environmental effects of herbicides coupled with its high cost and inadequate application knowledge, its adoption and usage was highly constrained. PRACTICES have positive and significant impact on technical efficiency in all three models and also on CE in the two DEA models. Solis *et al.* (2009) found similar impact on TE. We note economic and environmental sustainability can be viewed as complementary rather than competitive goals.

6. Conclusions and Policy Implications

The study analyses impact of technological innovations on technical, allocative and cost efficiency of maize farmers in Benue State, Nigeria. The performance of parametric stochastic distance function (SIDF) with its non-parametric counterpart (VRS and CRS DEA) in predicting efficiency levels and identifying the sources were compared. The three models depict the existence of substantial technical, allocative and cost inefficiency in maize production in Benue State, Nigeria implying a considerable potential for enhancing productivity through improved efficiency. A t-test of equality in means and Wilcoxon signed-rank test of equality in distribution within bilateral pairs of employed approaches show significant differences in the efficiency estimated by the different approaches. However, given that in policy analysis, the ranking of efficiency scores may be more important than the quantitative estimates, a Spearman rank correlation analysis was conducted and results show significant similarities in the ranking. Results show that technological innovation variables such as hybrid seed, fertilizer, herbicides and conservation practices have positive and significant impact on one or more of the efficiency measures in all three models. These findings justify a further investment in agricultural research and development by the Nigeria Government and relevant private organisations. It was also found that education, extension contact, age, membership in farmer organization, access to credit, household size and off-farm work have significant impact on efficiency. The overall policy implication of our findings is that appropriate technology policy formulation and implementation is an effective instrument to improvement in farm efficiency and all things being equal, this is expected to result in increased productivity, food security and poverty reduction in Nigeria. The findings are robust to different methodological approaches.

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