Technological innovation and efficiency in the Nigerian maize sector: Parametric stochastic and non-parametric distance function approaches

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ABSTRACT

The current world food crisis has necessitated alternative policy actions in most countries, including increased investment in agricultural research and development. This study uses duality theory to obtain allocative and cost efficiency from the parametric stochastic distance function, and results are then compared to estimates from the non-parametric distance function. The study further evaluates the impact of technological innovations and other policy variables on technical, allocative and cost efficiency from both approaches in a second-stage endogeneity-corrected Tobit regression model. Mean technical, allocative and cost efficiency ranges from 80.1 per cent to 86.7 per cent, from 57.8 per cent to 73.8 per cent, and from 50.3 per cent to 62.3 per cent respectively. The analysis of technical, allocative and cost efficiency with respect to technological innovation and other policy factors is robust. Results show that policies aimed at maize technology development and its timely dissemination, as well as improvements in education and access to credit and extension, could promote technical, allocative and cost efficiency, reduce yield variability, enhance farm income and food security and reduce poverty in Nigeria.

Keywords: technology, efficiency, maize, parametric, non-parametric, distance function, Nigeria

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1 INTRODUCTION

The current global food crisis has raised concern among policymakers in countries around the world. The crisis is caused by a web of interconnected forces involving agriculture, energy, climate change, trade and new market demands from emerging markets (CSIS, 2008). Improving agricultural productivity is therefore considered one of the major solutions when it comes to effectively addressing rising food prices. Maize is one of the world's main staple crops, ranking third after sorghum and millet on the list of cereal crops, and featuring as one of the five food crops promoted in the attainment of food self-sufficiency in Nigeria (FAO, 2009; Sayyadi, 2008). In Nigeria, maize accounts for about 43 per cent of calorie intake while contributing 7.7 per cent to the total cash income of farm households (Nweke, 2006; Nweke, Lynam & Spencer, 2002). Maize also serves as a commercial crop and comprises about 80 per cent of poultry feed (FAO, 2008). Maize is therefore considered 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 the average yield is 1.5 tonnes/ha. The average yield is low compared to the world average of 4.3 tonnes/ha and to that of other African countries such as South Africa with 2.5 tonnes/ha (FAO, 2009). The gap between maize supply and demand has been steadily growing. The short supply of maize is evident in frequent maize price increases in Nigeria. In view of the high demand for maize, the government of Nigeria initiated a programme in 2006 aimed at doubling maize production in the country, for both national consumption and international export, through the promotion of improved agricultural technologies such as fertilisers, hybrid seeds, pesticides, herbicides and better management practices (USAID, 2006). Since then, several stakeholders have expressed support for this programme, as it is expected to enhance food security, increase import substitution and earn foreign exchange for the country (IITA, 2007).

Technological innovation often comes at a cost, and so determining its impact on farm households is crucial for policy analysis. This study focuses on the impact of technological innovation on the efficiency of farm households. Policy conclusions may vary depending on the methodology used. However, consistency of results from different approaches validates policy conclusions. The literature on efficiency analysis usually follows two broad approaches, namely the parametric approach and the non-parametric approach. The parametric approach could either be stochastic or deterministic. Whereas the stochastic frontier accounts for noise in the data, the deterministic frontier does not; rather, all deviations of output from the frontier are attributed to inefficiency. The disadvantages of the parametric stochastic approach are the need for assumptions about the production technology and the distribution of the two error components. In terms of the parametric approach, the production technology is represented by either a production or a cost function. Recently, distance functions are also used in efficiency analysis. Data envelopment analysis (DEA) is the most commonly used non-parametric frontier approach. The major disadvantage of the DEA approach is that it takes no account of the possible influence of measurement errors and other noise in the data. However, it has the advantage of removing the necessity of making arbitrary assumptions about the functional form of the frontier, as well as distributional assumptions about the error terms.

This paper employs the theory of duality to obtain a cost function and derive allocative and cost efficiency from the parametric stochastic input distance function (SIDF). Efficiency scores from the SIDF are compared to those from the non-parametric counterpart, i.e. DEA. Furthermore, the impact of technological innovation on efficiency is compared in terms of the different approaches taken. 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 those of Alene and Manfred (2005), Alene, Manyong and Gockowski (2006) and Herrero (2005). Similar studies in other sectors are those of Coelli and Perelman (1996, 1999, 2000) and Cuesta, Lovell and Zofio (2009). All the aforementioned studies compared only technical efficiency estimates from different approaches. However, 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 the economic or cost efficiency of farmers implied by the economic theory of production. All the studies mentioned, with the exception of those of Cuesta et al. (2009) and Herrero (2005), compared results from deterministic distance functions with other approaches. Given the uncertainties surrounding agricultural production, the modelling of efficiency in a stochastic distance function framework is necessary.

The remainder of the paper is organised as follows: The analytical framework is presented in section 2, the empirical model in section 3, and data and variable descriptions in section 4. In section 5, efficiency scores from SIDF and DEA models are compared and all Tobit results are presented and analysed. 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 Shephard (1953). Whereas the output distance function looks at the extent to which the output vector may be expanded with the input vector held fixed, the input distance function looks at the proportional contraction of the input vector with the output vector held fixed. The input distance function is appropriate if the firm has more control over inputs than outputs (Coelli, Prasada Rao & Battese, 2005). Based on this, the study employs the input orientation and therefore the discussion is limited to input distance function. In this study, parametric stochastic and non-parametric input distance functions are compared.

2.1 Parametric stochastic input distance function (SIDF)

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

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

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,

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

$D_I(x, y)$ 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 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 imposition of a functional form for $D_I(x, y)$ does not permit its direct estimation. A convenient way of dealing with this problem was suggested by Lovell, Richardson, Travers and Wood (1994), who exploited the property of linear homogeneity of the input distance function, expressed mathematically as:

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

Assuming one has access to cross-sectional data on N firms, producing M outputs using K inputs, setting $\lambda = 1/x_1$ and choosing a Cobb-Douglas functional form, then equation (3) can be expressed as:

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

where the distance term $-\ln(D_I)$ 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 an estimable equation in a stochastic frontier framework as:

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

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 be either half-normal distribution, i.e. $\left|N(0,\sigma_u{}^2)\right|$, exponential distribution, i.e. EXP$(\mu,\sigma_u{}^2)$, truncated normal, i.e. (($N(\mu,\sigma_u{}^2)$)) or gamma distribution. The predicted radial input-oriented measure of technical efficiency (TE) for a unit of analysis is given as:

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

Using the properties of the input distance function, the duality between the cost and input distance functions can easily be expressed in a general form as:

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

where C is the cost of production and w denotes a vector of input prices. Using the first-order condition for cost minimisation and making use of Shephard's Lemma, it is possible to calculate allocative efficiency (AE) and cost efficiency (CE).

2.2 Non-parametric distance functions (DEA)

DEA is a non-parametric approach to the distance function estimation (Fare et al., 1994). The purpose of this approach is to construct a non-parametric envelopment frontier over the data points so 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 for the reason stated in the previous section, the discussion is focused on the input-oriented 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 input-oriented constant returns to scale DEA frontier is defined by the solution of N linear programs of the form:

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

$$\text{subject to } \; -y_i + Y\lambda \geq 0,$$

$$\theta x_i - X\lambda \geq 0, \tag{8}$$

$$\lambda \geq 0$$

where θ is the input distance measure and λ is the Nx1 vector of constants. The value of θ is the efficiency score for the *i*th firm and will satisfy $0 \leq \theta \leq 1$, with a value of 1 indicating a point on the frontier and hence a technically efficient firm. Inefficient units can be transformed into efficient units by radially contracting their 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 the availability of price information, behavioural objectives can be considered, such as cost minimisation or revenue maximisation, thus allowing both technical and allocative efficiencies to be measured. In 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:

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

$$\text{subject to } \; -y_i + Y\lambda \geq 0,$$

$$x_i * - X\lambda \geq 0, \tag{9}$$

$$\lambda \geq 0$$

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 CE of the *i*th firm would be calculated as

$$CE = \frac{w_i' x_i *}{w_i' x_i} \tag{10}$$

Allocative efficiency is calculated as

$$AE = \frac{CE}{TE} \tag{11}$$

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

3 EMPIRICAL MODELS

In terms of the parametric approach, a Cobb-Douglas (CD) stochastic input distance function is assumed for this study. The use of distance function frontier is motivated because the direct estimation of cost frontiers is not appropriate when input prices do not differ among firms or when there is systematic deviation from cost-minimising behaviour (Bauer, 1990). The problem with the production frontier (see, for example, Bravo-Ureta & Rieger, 1991) is that a production function is estimated when one is clearly assuming that the input quantities are decision variables, thus exposing the approach to criticism to the effect that simultaneous equation bias may afflict the production frontier and that the efficiency estimates may be biased (Alene & Hassan, 2005; Coelli, Fleming & Singh, 2003). The distance function approach does not suffer from similar problems. The CD is self-dual and permits an easy decomposition of the cost function and derivation of allocative efficiency. However, the specification is admittedly restrictive in terms of the maintained properties of the underlying production technology. Therefore, a likelihood ratio test was conducted to test the hypothesis that the CD functional form is not an adequate representation of the data for maize farmers in Benue State, Nigeria, given the specification of the more flexible translog form. This hypothesis could not be rejected at the 5 per cent level of significance. Therefore the CD is retained.

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

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

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 fertiliser, and index of other inputs such as seed, pesticides and herbicides. ln represents natural logarithm, while δ, α and β_j are unknown parameters to be estimated.

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

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

one obtains:

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

The unobservable distance term "$-\ln \mathrm{D_i}$" represents a random term and can be interpreted as the traditional stochastic frontier analysis 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) is 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 per cent level of significance. The input-oriented TE scores are predicted using the conditional expectation predictor:

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

Developments in duality theory and functional form specification permit the derivation of the parameters of a cost function from the production function and vice versa (Bravo-Ureta & Rieger, 1991; Heathfield & Wibe, 1987; Schmidt & Lovell, 1979). To derive the dual cost function, the distance in equation (12) is firstly set to one in order to obtain the equation of the production surface. Secondly, one of the inputs is made the subject of the formula, and the partial derivatives of the other inputs with respect to this are derived. Thirdly, using j-1 first-order conditions for cost minimisation, the cost identity and the linear homogeneity condition, j equations in j unknowns, are obtained and these are solved for each input, x, using matrix algebra. Again using the homogeneity condition, the solution of each input x is substituted in equation (12) to arrive at the cost function, and this is defined as:

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

where C_i is the production cost of maize for the *i*th farmer; W_{ji} is the *j*th input price, which includes the price of land, labour and inorganic fertiliser and the price index for other inputs; and b_0, b_j and ϕ are unknown parameters derived from the primal function. The parameters of the cost and input distance function are related as follows:

$$b_j = \hat{\beta}_j, \ \phi = -\hat{\alpha}, \text{ and } b_0 = -\hat{\delta} - \sum_{j=1}^{4} \hat{\beta}_j \ln(\hat{\beta}_j)$$

The technically efficient input quantities are predicted as follows:

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

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

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

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 of the *i*th farmer is $\hat{X}_i^C \cdot W_i$, while the observed cost of production is $X_i \cdot W_i$. These two cost measures are then used to calculate the CE scores for the *i*th farmer:

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

AE is calculated residually as:

$$A\hat{E}_i = \frac{C\hat{E}_i}{T\hat{E}_i}, \tag{21}$$

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

In terms of 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, the same output variables and the same input variables as in the SIDF.

To analyse the impact of technological innovation (hybrid seed, inorganic fertiliser, 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 zero and one. The Tobit model is specified as:

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

where Y_i^* is a latent variable representing the efficiency measure for each farm household, X_i is an $nx1$ 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 are $kx1$ and $mx1$ vectors of unknown parameters to be estimated, u_i is 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 was tested using the instrumental variable approach as proposed by Smith and Blundell (1986). To correct for endogeneity, this study followed a two-step approach in which each endogenous technology variable was estimated in a first stage and the predicted values included in a second step as additional explanatory variables, yielding unbiased estimates of the impact of technological innovation on efficiency.

4 DATA AND VARIABLES

The study was conducted in Benue State, Nigeria. Given the lack of farm records and the inadequacy of the disaggregated household survey data available, a field survey method of gathering information was adopted. A multistage stratified sampling procedure was employed in selecting the respondents for this study. Interviews were conducted with a total of 240 smallholder farm households located in the four local government areas of Benue State.

Data on the output and input quantities and prices used by the farm households was collected using structured questionnaires based on the farmers' memory recall. Table 1 provides a description and the mean values of the variables used in the analysis. One output variable (PROD) and four input variables (LAND, LABOUR, FERT and OTHER) were used in estimating the frontier models. Information on input and output quantities in kilograms was elicited using the prevailing local measure in the study area, i.e. a 25 kg basin. For instance, a farmer was asked to recall how many basins of maize he/she had harvested during the previous planting season, and the given figures were converted to standard metrics. Likewise, all area measurements were captured using the local method of counting the rows planted, with 100 rows equivalent to one hectare.

The observed average price per unit of inputs used was employed in the analysis. For instance, farmers were asked how much it costs to rent one hectare of farmland in the area during the cropping season, irrespective of whether they were renting their own farms, and the average was then computed. With respect to labour, some farmers used only family labour, while others used both family and hired labour, but the average farmer is aware of the cost of hiring labour in his or her area. The mean response to the cost of labour per day was computed after adjusting for adult and man equivalents. Since all the farmers were using land

and labour, all had a value for the price of land and labour. Fertiliser and other inputs are usually sold on the open market, and therefore the average price per unit used was calculated. In the case of a farmer not using a particular purchased input, the price value for that input was recorded as zero.

Four variables indexing technological innovation, namely HYV, AFERT, HERB and PRACTICES, were included in the second-stage regression, along with the other variables AGE, GENDER, EDU, HHS, OFFWORK, MFG, EXT, CREDIT and MARKET. The average age of the farmers interviewed was 47 years, showing that the majority were still in their productive years. Educational level in the study area is low, with the respondents indicating an average of eight years of schooling, implying that most of the farmers had only completed their primary schooling. The area cultivated with maize is very small at an average of 1.2 hectares. The average household size was recorded as 12 persons, pointing to an abundance of family labour.

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

Table 1: Description and summary statistics of variables used in the analysis

Variable	Description	Mean
PROD	Quantity of maize in kilograms produced during 2008/2009 farm season	1320.38
LAND	Area of land in hectares cultivated with maize	1.208
LABOUR	Number of man-days worked by both family and hired labour	111.195
FERT	Amount in kilograms of inorganic fertiliser used	115.185

OTHER	Fisher quantity index of seed, herbicides and pesticides used	56.343
WLAND	Rental price in naira of one hectare of farmland	4989.167
WLABOUR	Price or cost in naira of labour per day	89.808
WFERT	Price in naira of inorganic fertiliser per kilogram	57.899
WOTHER	Implicit price index of seed, herbicides and pesticides derived by dividing the cost of other inputs by OTHER	68.638
AGE	Age in years of household head	47.167
GENDER	1 = household head is male; 0 otherwise	0.888
EDU	Number of years of formal education completed by household head	8.433
HHS	Number of persons in household	11.742
OFFWORK	1 = engagement in off-farm work; 0 otherwise	0.675
MFG	1 = household head is a member of any farmers' organisation; 0 otherwise	0.454
EXT	Number of extension visits during cropping period	2.546
CREDIT	1 = farmer has access to credit; 0 otherwise	0.138
MARKET	Distance in kilometres to nearest market	6.278
HYV	Area in hectares of maize farm cultivated with hybrid seed variety	0.895
AFERT	Area in hectares of maize farm subject to inorganic fertiliser application	0.816
HERB	Area in hectares of maize farm subject to herbicide application	0.591
PRACTICES	Number of conservation practices adopted by the farmer on his/her maize farm	1.75

5 ESTIMATION RESULTS

5.1 MLE estimates of parametric stochastic input distance function

Table 2 presents both the maximum likelihood (ML) and the ordinary least square (OLS) estimates of the SIDF using the computer program FRONTIER v. 4.1 developed by Coelli (1996). Results show that all variables are significant at 1 per cent and have expected signs. The estimated coefficient of output is less than one in absolute terms, indicating increasing returns to scale. It should be stressed here that the homogeneity restriction on the input coefficients of the SIDF does not translate to constant returns to scale, as is the case with the conventional production function. For the SIDF, returns to scale is computed as the inverse of the negative of the output coefficient (Coelli et al., 2005), which is 1.351 (i.e. -(-1/0.729)) for this study. 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 per cent increase in maize output results in a 7.4 per cent 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 example, the elasticity with respect to land is largest with a value of 0.67, meaning that the cost of that input represents 67 per cent of total cost at the sample mean.

Table 2: MLE and OLS estimates of parametric SIDF

Variable	Mean	Parameter	OLS estimates	ML estimates
INTERCEPT		δ	3.718***	3.883***
			(0.200)	(0.216)
PROD	1320.38	α	-0.729***	-0.740***
			(0.021)	(0.021)
LAND	1.208	β_1	0.679***	0.667***
			(0.022)	(0.024)
LAB	111.195	β_2	0.219***	0.233***
			(0.021)	(0.023)
FERT	115.185	β_3	0.036***	0.038***
			(0.003)	(0.003)
OTHER	56.343	β_4	0.067	0.061 [a]
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 it is significant at 1 per cent, implying that 83 per cent 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. The LR test statistic is 13.23, which is significant when compared with the 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 and the observed average input prices, the parameters of the corresponding dual cost function were derived, thus forming the basis for computing the CE and AE. The dual cost frontier is given as:

$$\begin{aligned} \ln C_i &= -2.977 + 0.667 \ln W_{Land} + 0.233 \ln W_{Labour} + 0.038 W_{Fert} \\ &+ 0.061 \ln W_{Other} + 0.740 \ln PROD_i \end{aligned} \tag{23}$$

where C is the cost of production for the *i*th farmer. W_{Land} is the rental price of land per hectare estimated at ₦4989.17 . W_{Labour} is the price of labour per day estimated at ₦ 89.81.

W_{Fert} is the price of inorganic NPK fertiliser per kg estimated at ₦57.9. W_{Other} is the implicit price index of other inputs estimated at ₦68.64 per kg.

5.2 Comparison of efficiency scores and distribution

Policy conclusions may vary depending on the methodology used. However, consistency of results from different approaches validates policy conclusions, hence the reason for the comparative analysis. Whereas SIDF characterises economies of scale that apply to the whole sample of data, DEA characterises economies of scale for individual observations. DEA classified 60.4 per cent, 3.8 per cent and 35.8 per cent of farmers as operating under increasing, decreasing and constant returns to scale respectively. This confirms the SIDF result that the farmers were on average operating under increasing returns to scale.

The frequency distribution of technical, allocative and cost efficiency from SIDF and DEA models on the entire sample is presented in Table 3. The average TE from SIDF, VRS DEA and CRS DEA is 86.7 per cent, 85.5 per cent and 80.1 per cent respectively. This implies that for the SIDF, VRS DEA and CRS DEA, a cost saving of 13.3 per cent, 14.5 per cent and 19.9 per cent respectively could be achieved by improving TE without reducing output. The average AE from SIDF, VRS DEA and CRS DEA is 57.8 per cent, 73.8 per cent and 65.9 per cent respectively. This implies that for the SIDF, VRS DEA and CRS DEA, a cost saving of 42.2 per cent, 26.2 per cent and 33.1 per cent respectively could be achieved by improving allocative efficiency without reducing output. The average CE from SIDF, VRS DEA and CRS DEA is 50.2 per cent, 62.3 per cent and 51.6 per cent respectively. This implies that for the SIDF, VRS DEA and CRS DEA, a cost saving of 49.1 per cent, 37.7 per cent and 48.4 per cent respectively could be achieved by improving cost efficiency without reducing output.

Table 3: 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, it is observed that SIDF produces higher technical efficiency values than the two DEA models. DEA attributes all deviations from the frontier to inefficiencies, whereas SIDF includes some random errors, hence the higher efficiency scores from the latter. The VRS DEA and CRS DEA exhibit greater variability than the SIDF efficiency measures. The broader spread of efficiencies may well also account for the greater variances. Maize farmers in Benue State operate with considerable inefficiency dominated by cost inefficiency, as depicted by all approaches.

From Table 3, it appears that 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 was 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 4 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 per cent. The differences in the efficiency scores arise from the fact that DEA attributes all deviations from the frontier to inefficiency, whereas SIDF attributes deviations partly to inefficiency and partly to some random errors that are beyond the farmer's control. The Wilcoxon test further reinforces this result by indicating that the distributions within the bilateral pairs of results are also statistically different.

Table 4: Tests of hypothesis between efficiency scores from SIDF and DEA

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

Although the different approaches produced efficiency measures quantitatively different from one another, it is still possible to achieve consistency of results with respect to the ranking of individual farm households, which in many policy analyses may be more important than the quantitative estimates of efficiency. Therefore, to assess the overall consistency of the three methods in ranking individual farms in terms of efficiency, the coefficient of Spearman's rank-order correlation was calculated between the three models. Spearman's correlation suggests that the different farm households rank similarly when they are ordered according to either their parametric or nonparametric efficiency scores. Based on this, one can draw valid policy conclusions from the results of this study.

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

Summary results for the exogeneity test on the technological innovation variables are presented in Table 5. It is observed that the exogeneity of each variable in each model was rejected in at least one case. An endogeneity-corrected Tobit model was employed in the second-step regression in the case of rejection of the null hypothesis.

The results of the second-stage endogeneity-corrected Tobit model are presented in Table 6. 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 could be positive or negative, but in this study it had a positive and significant impact on TE in all three models and a positive and significant impact on CE in the VRS DEA model. This could be due to the fact that the older farmers were in the farm business first and therefore had better access to land and other production inputs.

Table 5: Summary results of Smith-Blundel test of exogeneity

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

In this study, the relationship between LAND and the three efficiency measures in all three models was found to be inconsistent. Whereas this has a negative and significant impact on technical efficiency in the SIDF model, it has a positive and significant impact on technical and cost efficiency in the VRS DEA model and a positive and significant impact on all three efficiency measures in the CRS DEA model. A similar contrasting result was found by Coelli, Rahman and Thirtle (2002) for modern boro rice farmers in Bangladesh. The relatively consistent positive and significant relationship in the allocative and cost efficiency measures implies that farmers with larger farm sizes are more efficient in choosing cost-minimising input combinations. It then appears that small-scale operations are a source of inefficiency and hence low productivity in the area. OFFWORK can increase productivity by producing income that can be used to purchase modern inputs. Here, it was consistently negative but with a significant impact on technical efficiency only in both the SIDF and VRS DEA models. This implies that farmers who engage in off-farm work are likely to be less efficient in farming. It could be that the labour used for non-farm work is being improperly allocated to farming.

Table 6: **Endogeneity-corrected Tobit results of determinants of TE, AE and CE**

Variable	SIDF			VRS DEA			CRS DEA		
	TE Coeff.	AE Coeff.	CE Coeff.	TE Coeff.	AE Coeff.	CE Coeff.	TE Coeff.	AE Coeff.	CE Coeff.
GENDER	-0.013	0.012	0.000	-0.037	0.011	-0.010	-0.044	0.019	-0.007
	(0.009)	(0.019)	(0.017)	(0.030)	(0.032)	(0.022)	(0.034)	(0.032)	(0.017)
AGE	0.002***	-0.000	0.001	0.004***	0.001	0.001**	0.004***	-0.002	0.001
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
EDU	0.002***	0.000	0.001	0.004**	0.001	0.001	0.004***	0.002	0.001
	(0.000)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)
HHS	0.001***	0.001	0.001*	0.000	0.001	0.001	0.003*	0.001	0.002***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
LAND	-0.034***	0.045**	0.025	0.071**	-0.003	0.036*	0.152***	0.072**	0.123***
	(0.008)	(0.020)	(0.018)	(0.029)	(0.030)	(0.021)	(0.034)	(0.030)	(0.018)
OFFWORK	-0.010*	-0.005	-0.009	-0.037*	-0.003	-0.018	-0.025	-0.002	-0.012
	(0.006)	(0.013)	(0.012)	(0.020)	(0.021)	(0.015)	(0.023)	(0.021)	(0.012)
MFG	0.045***	0.002	0.028	0.059*	0.019	0.027	0.111***	0.041	0.039***
	(0.010)	(0.021)	(0.019)	(0.033)	(0.035)	(0.025)	(0.037)	(0.035)	(0.019)
EXT	-0.003**	0.007*	0.004	0.002	0.007	0.007*	-0.005	0.009	0.002
	(0.002)	(0.004)	(0.003)	(0.006)	(0.006)	(0.004)	(0.006)	(0.006)	(0.003)
CREDIT	0.023***	0.129***	0.130***	0.044	0.170***	0.177***	0.025	0.176***	0.131***

	(0.008)	(0.018)	(0.016)	(0.028)	(0.029)	(0.021)	(0.032)	(0.029)	(0.016)
MARKET	-0.000	-0.000	-0.000	-0.003*	-0.001	0.001	-0.002	-0.001	-0.001
	(0.000)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)
HYV	0.011**	0.034***	0.035***	0.024	0.046**	0.018	0.038*	0.063***	0.035***
	(0.006)	(0.013)	(0.011)	(0.020)	(0.021)	(0.014)	(0.022)	(0.021)	(0.011)
AFERT	0.018**	0.057**	0.060***	0.029	0.078**	0.053**	0.027	0.107***	0.091***
	(0.009)	(0.027)	(0.024)	(0.029)	(0.032)	(0.023)	(0.035)	(0.032)	(0.024)
HERB	0.008	-0.014	-0.005	0.000	-0.030	-0.019	0.054**	-0.031	0.008
	(0.006)	(0.013)	(0.008)	(0.014)	(0.023)	(0.016)	(0.025)	(0.022)	(0.008)
PRACTICES	0.009***	0.002	0.006	0.024***	0.002	0.010*	0.018**	0.002	0.007*
	(0.002)	(0.005)	(0.004)	(0.007)	(0.008)	(0.005)	(0.008)	(0.008)	(0.004)
INTERCEPT	0.750***	0.431***	0.305***	0.592***	0.689***	0.388***	0.400***	0.501***	0.163***
	(0.019)	(0.041)	(0.038)	(0.065)	(0.068)	(0.047)	(0.074)	(0.069)	(0.038)
LLF	417.474	234.686	259.949	38.538	112.307	194.421	32.413	113.035	258.991
LR TEST	293.72***	139.09***	196.07***	104.400***	66.090***	168.110***	106.510***	122.850***	318.070***

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

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

The extension variable EXT presents somewhat of a puzzle. It was expected to be positive, as it enhances farmers' access to information and improved technological packages. Whereas it had a negative and significant impact on TE in the SIDF model, it had a positive and significant impact on AE and CE in the SIDF and VRS DEA models respectively. Some researchers in Nigeria (Ogunyinka & Ajibefun, 2004; Okoye, Onyenweaku & Asumugha, 2006) found similar negative signs of the extension variable for technical efficiency. This negative impact can be explained by the fact that extension services in Nigeria in general have not been effective, especially after the withdrawal of World Bank funding from the Agricultural Development Project (ADP), which is the main agency responsible for extension services. Given this problem of inadequate funding of the extension outfit, the dissemination of agricultural innovation to farmers is in most cases done at the wrong times, and farmers do not have access to yield-improving inputs at the right times. More so, when extension agents do not have new information for farmers, contact with those agents would only amount to a waste of resources, leading to a negative impact.

CREDIT was consistently positive and had a significant impact on AE and CE in all three models, but was significant for TE in the SIDF model only. The availability of credit loosens production constraints, thus facilitating the timely purchase of inputs and improving productivity via efficiency. This 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 efficient than farms located further away from the market. Distance from the market might raise production costs and 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, although significant in the SIDF TE model only. In all cases, GENDER was not found to be significant.

Finally, an important goal of this study was to evaluate explicitly the impact of technological innovation on the efficiency of maize farmers. The results show that HYV has a positive and significant impact on TE, AE and CE in the SIDF and CRS DEA models, but a significant impact only on AE in the VRS DEA model. Chirwa (2007) and Zavale, Mabaya and Christy (2006) found a 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 federal government's current programme of doubling maize production. AFERT was also found to have a positive and significant impact on AE and CE in all three models, but a significant impact on TE in the SIDF model only. These findings are consistent with those of Msuya, Hisano and Nariu (2008) and Okoye et al. (2006), namely that inorganic fertiliser has a positive impact on AE and TE respectively. Fertiliser technology can be said to correlate with credit. Thus, failure to use fertiliser may result in an irrecoverable loss in output.

The use of herbicide can have negative or positive correlation with output and efficiency, depending on whether it is used proactively or reactively. The variable HERB was found to have a positive and significant impact on TE in the SIDF model. In most cases, it had a negative though not significant impact on AE and CE in all three models. It could be that due to the farmers' perceptions of the health and environmental effects of herbicides, coupled with the high cost thereof and inadequate application knowledge, the adoption and usage of herbicides has been highly constrained. Moreover, if it is used only by those who have suffered a weed infestation, the relationship will be negative. PRACTICES had a positive and significant impact on TE in all three models and also on CE in the two DEA models. Solis, Bravo-Ureta and Quiroga (2009) found a similar impact on TE. It is noted that economic and environmental sustainability can be viewed as complementary rather than competitive goals.

6 CONCLUSIONS AND POLICY IMPLICATIONS

The study derived allocative and cost efficiency from stochastic input distance function using duality theory, and further analysed the impact of technological innovations on the technical, allocative and cost efficiency of maize farmers in Benue State, Nigeria. The performance of

SIDF, VRS and CRS DEA in predicting efficiency levels and identifying the sources was compared. The three models depict the existence of substantial technical, allocative and cost inefficiency in maize production in Benue State, implying a considerable potential for enhancing productivity through improved efficiency. A t-test of equality in means and a Wilcoxon signed rank-test of equality in distribution within bilateral pairs of employed approaches showed significant differences in 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, Spearman's rank correlation analysis was conducted, with the results showing significant similarities in the ranking. It was found that technological innovation variables such as hybrid seed, fertiliser, herbicides and conservation practices have a 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 Nigerian government and relevant private organisations. It was also found that education, extension contact, age, land, membership of farmers' organisations, access to credit, household size and off-farm work have a significant impact on efficiency. The overall policy implication of the findings of this study is that appropriate technology and complementary policy formulation and implementation is an effective instrument to improve farm efficiency. All things being equal, this is expected to result in increased productivity, improved food security and the reduction of poverty in Nigeria. The findings are robust to different methodological approaches.

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REFERENCES

Alene, D.A. & Hassan, R.M. 2005. The efficiency of traditional and hybrid maize production in eastern Ethiopia: Extended efficiency decomposition approach. *Journal of African Economies,* 15(1): 91–116.

Alene, D. A. & Manfred, Z. 2005. Technology adoption and farmer efficiency in multiple crop production in eastern Ethiopia: A comparison of parametric and non-parametric distance functions. *Agricultural Economics Review*, 6(1): 5–19.

Alene, D.A.; Manyong, V.M. & Gockowski, J. 2006. The production efficiency of intercropping annual and perennial crops in southern Ethiopia: A comparison of distance functions and production frontiers. *Agricultural Systems,* 91: 51–70.

Bauer, P.W. 1990. Recent developments in the econometric estimation of frontiers. *Journal of Econometrics*, 46: 39–56.

Bravo-Ureta, B.E. & Rieger, L. 1991. Dairy farm efficiency measurement using stochastic frontiers and neoclassical duality. *American Journal of Agricultural Economics*, 73(2): 421–428.

Chirwa, E.W. 2007. Sources of technical efficiency among smallholder maize farmers in southern Malawi. AERC Research Paper, 172. Available online at: http://www.aercafrica.org/documents/RP172.pdf (Accessed: 15 March 2009).

Coelli, T.J. 1996. A guide to FRONTIER 4.1: A computer program for stochastic production and cost function estimation. CEPA Working Papers, No. 7.

Coelli, T.J.; Fleming, E. & Singh, S. 2003. *An input distance function approach to the measurement of technical and allocative efficiency*. Contributed paper presented at the 8th European Workshop on Efficiency and Productivity Analysis, Oviedo, September 2003.

Coelli, T.J. & Perelman, S. 1996. Efficiency measurement, multi-output technologies and distance functions: With application to European railways. *CREPP Working Paper 96/05*. Liege: University of Liege.

Coelli, T.J. & Perelman, S. 1999. Theory and methodology: A comparison of parametric and non-parametric distance functions: With application to European railways. *European Journal of Operational Research*, 117: 326–339.

Coelli, T.J. & Perelman, S. 2000. Technical efficiency of European railways: A distance function approach. *Applied Economics,* 32: 1967–1976.

Coelli, T.J.; Prasada Rao, D.S. & Battese, G.E. 2005. *An introduction to efficiency and productivity analysis.* 2nd edition. Norwell: Kluwer Academic Publishers.

Coelli, T.J.; Rahman, S. & Thirtle, C. 2002. Technical, allocative, cost and scale efficiencies in Bangladesh rice cultivation: A non-parametric approach. *Journal of Agricultural Economics,* 53(3): 607–626.

CSIS (Centre for Strategic and International Studies). 2008. *A call for a strategic US approach to the global food crisis: A report of the CSIS task force on the global food crisis, core findings and recommendations*. Washington DC: CSIS.

Cuesta, R.A.; Lovell, C.A.K. & Zofío, J.L. 2009. Environmental efficiency measurement with translog distance functions: A parametric approach. *Ecological Economics,* 68: 2232–2242.

FAO (Food and Agriculture Organisation). 2008. *Global information and early warning system on food and agriculture: World Food Programme (GIEWS) – Special report on markets, prices and food situation for Benin, Niger and Nigeria*. Rome: FAO.

FAO (Food and Agriculture Organisation). 2009. *FAOSTAT, production statistics*. Available online at: http://faostat.fao.org/site/567/default.aspx#ancor (Accessed: 24 April 2009).

Färe, R., Grosskopf, S. & Lovell, C.A.K. 1994. *Production frontiers.* Cambridge University Press, Cambridge.

Heathfield, D. & Wibe, S. 1987. *An introduction to cost and production functions*. London: Macmillan.

Herrero, I. 2005. Different approaches to efficiency analysis: An application to the Spanish trawl fleet operating in Moroccan waters. *European Journal of Operational Research*, 167: 257–271.

IITA (International Institute of Tropical Agriculture). 2007. *Doubling maize production in Nigeria in two years*. Available online at: www.iita.org (Accessed: 5 November 2008).

Lovell, C.A.K.; Richardson, S.; Travers, P. & Wood, L.L. 1994. Resources and functionings: A new view of inequality in Australia. In: W. Eichlorn (Ed.). *Models and measurement of welfare and inequality.* Berlin: Springer-Verlag.

Msuya, E.E.; Hisano, S. & Nariu, T. 2008. *Explaining productivity variation among smallholder maize farmers in Tanzania*. Available online at: http://mpra.ub.uni-muenchen.de/14626/ (Accessed: 10 March 2009).

Muhammad, I.J. 2009. *Efficiency analysis of cotton-wheat and rice-wheat systems in Punjab, Pakistan*. Unpublished PhD Thesis. University of Agriculture, Faisalabad.

Nweke, F.I. 2006. New challenges in the cassava transformation in Nigeria and Ghana. *EPTD Discussion Paper No. 118*. Washington DC: International Food Policy Research Institute.

Nweke, F.I.; Lynam, J.K. & Spencer, D.S.C. 2002. *The cassava transformation: Africa's best-kept secret*. Lansing, MI: Michigan State University Press.

Ogunyinka, E.O. & Ajibefun, I.A. 2004. Determinants of technical inefficiency on farm production: Tobit analysis approach to the NDE farmers in Ondo State, Nigeria. *International Journal of Agriculture and Biology,* 2: 355–358.

Okoye, B.C.; Onyenweaku, C.E. & Asumugha, G.N. 2006. Allocative efficiency of small-holder cocoyam farmers in Anambra State, Nigeria. *MPRA Paper No. 17362*. Available online at: http://mpra.ub.uni-muenchen.de/17362/ (Accessed: 12 April 2010).

Oyewo, I. O. & Fabiyi, Y.L. 2008. Productivity of maize farmers in Surulere Local Government Area of Oyo State. *International Journal of Agricultural Economics and Rural Development*, 1(2): 25–34.

Sayyadi, A.R. 2008. Nigeria aims to be self-sufficient in the production of basic food sources. *Trade Invest Nigeria* (11 March 2008). Available online at: http://www.tradeinvestnigeria.com/news/231171.htm (Accessed: 20 December 2008).

Schmidt, P. & Lovell, C.A.K. 1979. Estimating technical and allocative inefficiency relative to stochastic production and cost frontiers. *Journal of Econometrics*, 9: 343–66.

Shephard, R.W. 1953. *Cost and production functions*. Princeton, NJ: Princeton University Press.

Smith, R.J. & Blundell, R.W. 1986. An exogeneity test for the simultaneous equation Tobit model with an application to labour supply. *Econometrica*, 54: 679–685.

Solis, D.; Bravo-Ureta, B.E. & Quiroga, R.E. 2009. Technical efficiency among peasant farmers participating in natural resource management programmes in central America. *Journal of Agricultural Economics*, 60(1): 202–219.

USAID (United States Agency for International Development). 2006. Trip Report: Northern Nigeria joint food supply assessment mission. Available online: at http://www.fews.net/docs/Publications/1001220 (Accessed: 9 June 2009).

Zavale, H.; Mabaya, E. & Christy, R. 2006. *Smallholders' cost efficiency in Mozambique: Implications for improved maize seed adoption*. Contributed paper prepared for presentation at the International Association of Agricultural Economists Conference. Gold Coast, Australia. 12–18 August 2006.