CHAPTER 4

ANALYTICAL FRAMEWORK AND EMPIRICAL SPECIFICATIONS

4.1 Introduction

Production efficiency has been measured using parametric and non-parametric approaches. Parametric methods include econometric estimation of production or cost functions. They represent single-output technologies and estimate the production frontier or curve which traces out the maximum feasible output for different input levels conditional on the technology in use. Transformations can be applied to multiple-output technology such that production and transformation functions yield optimal output given technology and resources (Andreu, 2008). These functions need to be estimated econometrically and can take several functional forms, ranging from the restrictive Cobb-Douglas to more flexible forms such the translog. Other functions related to production that can be econometrically estimated are cost functions, profit functions, and revenue functions. All of these can be formulated to account for multiple inputs and/or outputs. As in the case of production functions, these latter functions need to conform to certain properties in order to satisfy the economic concept they represent. In a set theory orientation, any production technology can be represented by output and input sets which need to satisfy some mathematical and economic properties to be an accurate representation of the production possibility frontier or curve. This approach is used in efficiency because of the relationship between technical efficiency and distance function. Distance functions are alternative representations of production technology that model multiple-input and multiple-output technological relationships. A disadvantage of the parametric approach is the imposition of an explicit functional form and a distributional assumption on the error terms.

In contrast, the non-parametric approach does not impose parametric restrictions on the underlying technology and therefore is less prone to misspecification. Data Envelopment Analysis (DEA) is the most common non-parametric approach. The choice between these approaches has been an issue of debate with some preferring the parametric approach while others prefer the non-parametric approach. Even within the class of parametric approaches, an interest is usually set on one approach against the other due to one limitation or the other. Given the different strengths and weaknesses of these approaches, it is of interest to compare their empirical performance using the same data set. In this study results from parametric stochastic input distance function is compared to those from non-parametric input distance frontier, the data envelopment analysis and parametric stochastic frontier production function. In the next section, the analytical framework of each approach is presented. The empirical models for this study are specified and described in section three.

4.2 Analytical Framework

4.2.1 The Production Frontier and Efficiency Decomposition

The production function is one of the conventional methods of representing the production technology. The use of production frontiers for decomposition of cost efficiency into its technical and allocative components was developed by Bravo-Ureta and Rieger (1991) to solve the problem of estimating a cost function directly when there is little or no variation in prices among sample firms. They followed a primal route in their methodology. The methodology involves using the level of output of each firm adjusted for statistical noise, the observed input ratio and the parameters of the stochastic frontier production function (SFPF) to decompose economic efficiency into technical and allocative efficiency. Then the cost function is analytically derived from the parameters of the SFPF. To illustrate the approach, a stochastic frontier production function is given as:

$$Y_i = f(X_i;\beta) + \varepsilon_i \tag{4.1}$$

$$\varepsilon_i = v_i - u_i \tag{4.2}$$

where ε_i is the composed error term. The two components v_i and u_i are assumed to be independent of each other, where v_i is the two-sided, normally distributed random error and u_i is the one-sided efficiency component with a half normal distribution. Y_i is the observed output of the ith firm, X_i is the input vector of ith firm and β is unknown parameters to be estimated.

The composed error (ε_i) is obtained by subtracting predicted output from the observed output:

$$\varepsilon_i = Y_i - \hat{Y}_i \tag{4.3}$$

The parameters of the SFPF were estimated using the maximum likelihood method. Subtracting v_i from both sides of the equation (4.2) results in

$$Y_i^* = Y_i - v_i = f(X_i;\beta) - u_i \tag{4.4}$$

where Y_i^* is the observed output of the *i*th firm adjusted for statistical noise captured by v_i. From equation (4.4), the technically efficient input vector, X_i^T, for a given level of Y_i^* is derived by solving simultaneously equation (4.4) and the input ratios, $X_1 / X_k = \rho_k (k > 1)$, where ρ_k is the ratio of the observed inputs.

Assuming the production function is self-dual function like the Cobb-Douglas production function , the corresponding dual cost frontier can be derived and written in a general form as:

$$C_i = h(W_i, Y_i^*; \delta) \tag{4.5}$$

where C_i is the minimum cost of the *i*th firm associated with output Y_i^*; W_i is a vector of input prices of the *i*th firm; and δ is a vector of parameters which are functions of the parameters in the production function.

The economically efficient (cost minimising) input vector, X_i^E, is derived by using Shephard's Lemma and then substituting the firm's input prices and adjusted output quantity into the system of demand equations:

$$\frac{\partial C_i}{\partial W_i} = X_i^E (W_i, Y_i^*; \delta) \tag{4.6}$$

For a given level of output, the corresponding technically efficient, economically efficient and actual costs of production are equal to $W_i X_i^T$, $W_i X_i^E$ and $W_i X_i$, respectively. These three cost measures are then used as the basis for calculating the technical and economic efficiency indices for the *i*th firm :

$$TE_i = \frac{W_i X_i^T}{W_i X_i} \tag{4.7}$$

and

$$EE_i = \frac{W_i X_i^E}{W_i X_i} \tag{4.8}$$

Following Farrel (1957), allocative efficiency can be calculated by dividing economic efficiency (EE) by technical efficiency (TE):

$$AE_i = \frac{W_i X_i^E}{W_i X_i^T} \tag{4.9}$$

Although, Bravo-Ureta and Rieger (1991) method was an attempt to resolve the problem of estimating a cost frontier directly, their methodology faced criticism because the parameters of the frontier are estimated using an output-oriented approach but technical efficiency is derived by imposing an input-oriented approach implied by the simultaneous solution of adjusted outputs and the observed input ratios to yield the technically efficient input vectors. This method will give technical efficiency scores that are very different from those obtained from the maximum likelihood estimation of the SFPF in equation (4.1) which is output-oriented unless the firms are operating under constant returns to scale. Even if the hypothesis of constant returns to scale is not rejected, consistent estimates cannot be obtained as long as the function coefficient is numerically different from unity (Alene, 2003; Alene and Hassan, 2005). Thus the estimates may suffer simultaneous equations bias because the production function was estimated when input quantities were clearly assumed to be the decision variables. That is, the endogenous input variables appear as regressors in the production function (Coelli et al., 2003).

4.2.2 Distance Function Approach to Efficiency Decomposition

Given the weaknesses in the cost decomposition using the stochastic frontier production function methodology, an alternative approach which avoids the simultaneous equation bias was proposed by Coelli et al. (2003). This methodology involves the use of distance functions. The notion of distance function was first introduced by Shephard (1953). The distance function can have either an output or input orientation. The output distance function measures how close a particular level of output is to the maximum attainable level of output that could be obtained from the same level of inputs if production is technically efficient. In other words, it represents how close a particular output vector is to the production frontier given a particular input vector (Mawson et al., 2003). An input-distance function is defined in a similar manner. However, rather than looking at how the output vector may be proportionally expanded with the input vector held fixed, it considers by how much the input vector may be proportionally contracted with the output vector held fixed. They are input-oriented because they try to find out how to improve the input characteristics of the firm concerned so as to become efficient. In most empirical studies, the selection of orientation is justified based on exogeneity/endogeniety argument for inputs and outputs. However, (Coelli, 1995b, Coelli and 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 functions.

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

$$D_I(x, y) = \max\{\rho : (x/p) \in L(y)\} \tag{4.10}$$

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,

$$L(y) = \{\ x \in R_+^K :\ x \text{ can produce y}\} \tag{4.11}$$

$D_I(x, y)$ is non-decreasing, positively linearly homogenous and concave in x, and non-increasing in y. 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 distance function has been estimated by different methods. These include the construction of parametric frontier using linear programming methods (Färe et al., 1994; Coelli and Perelman, 1999; Alene and Manfred, 2005); the construction of non-parametric piece-wise linear frontier using the linear programming method known as data envelopment analysis (DEA) (e.g. Färe et al., 1985, 1989, 1994; Coelli and Perelman, 1999; Alene and Manfred, 2005); estimation of parametric frontier using corrected ordinary least square (COLS) (e.g. Lovell et al., 1994; Grosskopf et al., 1997; Coelli and Perelman, 1999) and maximum likelihood estimation (MLE) of a parametric stochastic distance frontier (e.g. Coelli et al., 2003; Irz and Thirtle, 2004; Solis et al., 2009). ML of the parametric frontiers is preferred to COLS because of large mean square error advantages when γ^* is greater than 50 percent (Coelli, 1995). This study employs both the parametric stochastic input distance function (SIDF) and non-parametric input distance function, DEA approaches with the intent to make comparison of results. Results from the distance functions are further compared with those from conventional production frontiers.

4.2.2.1 The Parametric Stochastic Input Distance Function

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. Given a general form of an input distance function as:

$$D_I = f(x, y) \tag{4.12}$$

where f is a known functional form such as Cobb-Douglas or translog. Linear homogeneity implies:

$$\lambda D_I = f(\lambda x, y) \qquad \forall \lambda > 0 \tag{4.13}$$

Assuming x is a vector of K inputs and setting $\lambda = 1/x_1$, where x_1 is its (arbitrarily chosen) first component, then equation (4.13) can be expressed in a logarithmic form as:

$$\ln(D_I / x_1) = \ln f(x/x_1, y) \tag{4.14}$$

or

$$\ln(D_I) - \ln(x_1) = \ln f(x/x_1, y) \tag{4.15}$$

and hence

$$-\ln(x_1) = \ln f(x/x_1, y) - \ln(D_I) \tag{4.16}$$

where $-\ln(D_I)$ is defined as $\varepsilon = v - u$ to indicate that the distance term may be interpreted as a traditional stochastic frontier analysis disturbance term. That is, the distances in a distance function (which are radial distances between the data points and the frontier) could be due to either noise (v) or technical inefficiency (u) which is the standard SFA error structure (Coelli et al., 2003). Therefore equation (4.16) can be rewritten as:

$$-\ln(x_1) = \ln f(x/x_1, y) + v - u \tag{4.17}$$

The random errors, v are assumed to be independently and identically distributed as $N(0, \sigma^2{}_v)$ random variables and independent of the u's , which are assumed to be either 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 an ith firm is given as:

$$T\hat{E}_i = 1/\hat{D}_I = E[\exp(u_i) | v_i - u_i] \tag{4.18}$$

In other words, $1-T\hat{E}_i$ measures the proportion by which costs would be reduced by improving technical efficiency, without reducing output. A value greater than one for the input distance function ($\hat{D}_I$) indicates that the observed input-output vector is technically inefficient. When the producer is operating on the technically efficient frontier or the isoquant, the parametric input distance function attains a value of one.

The technically efficient input quantities can be predicted as follows:

$$\hat{x}_{ji}^T = x_{ji} \times T\hat{E}_i; \qquad j = 1,2...K \tag{4.19}$$

Using the first order condition for cost minimisation, the duality between the cost and input distance function can be derived (see Coelli et al. 2003 for derivation and explicit specification). The general form of the cost function is given as :

$$C_i(w_i, y_i) = \underset{x}{Min}\{w_i x_i : D_I(x_i, y_i) \geq 1\} \tag{4.20}$$

where C is the cost of production and w denotes a vector of input prices. From this minimisation problem, it is possible to relate the derivatives of the input distance function to the cost function and by making use of Shephard's Lemma, cost and allocative efficiency can be computed as in equations 4.34 and 4.35.

4.2.1.2 The Non-Parametric Input Distance Function

The input distance function can also be estimated through non-parametric techniques, such as Data Envelopment Analysis (DEA) and they are the reciprocal of the Debreu-Farrell technical efficiency measure (Lovell, 1993; Färe et al, 1994; Estache, et al., 2004). The original distance function by Shephard (1953) takes the (multiple) outputs as given and seeks to locate feasible contraction in the input vector, thus providing a complete characterization of an efficient production technology and a reciprocal measure of the distance of each producer to the efficient frontier (Färe et al., 1994).

Each DEA model tries to determine which firms form an envelopment (piecewise linear) of the technological set (the efficient frontier). Then DEA provides a methodology for the analysis of individual firms' efficiency relative to this (best-practice) frontier. Consequently, the selection of a particular DEA model involves a decision about the shape of the efficient frontier and another one about the distance concept used (Estache, et al., 2004). Thus, 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 DEA can either assume constant returns to scale (CRS) or variable returns to scale (VRS). The theoretical specification of an input distance function in a DEA framework consists of an optimization problem subject to certain constraints. 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 to N linear programs of the form:

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

$$\begin{aligned} \text{subject to } \quad & -y_i + Y\lambda \geq 0, \\ & \theta x_i - X\lambda \geq 0, \qquad (4.21) \\ & \lambda \geq 0 \end{aligned}$$

where θ is the technical 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. θ is therefore the proportion by which the observed inputs of the analysed firm could be contracted if the firm were efficient and therefore provides the input distance measure. λ is a Nx1 vector of intensity parameters that allows for convex combination of the observed inputs and outputs (in order to build the envelopment surface).

The input-oriented VRS model is solved by N linear programs of the form:

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

$$\text{subject to } -y_i + Y\lambda \geq 0, \quad \theta x_i - X\lambda \geq 0, \quad \lambda \geq 0, \quad N1'\lambda = 1 \tag{4.22}$$

where $N1'\lambda = 1$ is the convexity constraint which ensures that an inefficient farm is only benchmarked against farms of similar size and it is this additional constraint that makes equation (4.22) a VRS DEA. $N1'$ is an Nx1 vector of ones.

With availability of price information, both technical and allocative efficiencies can be measured. For the case of a CRS cost minimisation, one would run the input-oriented CRS DEA model set out in equation (4.21) to obtain technical efficiency scores. One would then run the following cost minimisation DEA

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

$$\text{subject to } -y_i + Y\lambda \geq 0, \quad x_i^* - X\lambda \geq 0, \quad \lambda \geq 0 \tag{4.23}$$

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 overall or cost efficiency of the *i*th firm is then calculated as

$$CE = \frac{w_i' x_i^*}{w_i' x_i} \tag{4.24}$$

Allocative efficiency is calculated as

$$AE = \frac{CE}{TE} \tag{4.25}$$

For a VRS cost-minimisation, equation (4.23) is altered by adding the convexity constraint, $N1'\lambda = 1$. The procedure for obtaining the allocative and cost efficiency under variable returns to scale is similar to that of the CRS DEA cost-minimisation problem.

4.3 Empirical Models

This section presents the empirical models employed for the study which are established based on the above framework. The specification begins with the distance functions followed by that of the conventional approach.

4.3.1 Parametric Stochastic Input Distance Function (SIDF)

The Cobb-Douglas (CD) parametric stochastic input distance function is assumed for this study. The specification is admittedly restrictive in terms of the maintained properties of the underlying production technology. However, 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 given the specification of the more flexible Translog (TL) form. This hypothesis could not be rejected at 5% level of significance. More over, a t-test was also conducted to test the hypothesis that efficiency scores from CD functional form are not statistically different from those from TL form. Again this hypothesis could not be rejected at 5% level of significance. Therefore CD was preferred based on these tests results and given TL's susceptibility to multicollinearity (Coelli, 1995b; Seymoun et al., 1998; Hassine-Belghith, 2009). Moreover, the main advantage of TL is its flexibility, but at the same time its main disadvantage is that it does not easily permit the decomposition of and identification of allocative efficiency as the CD does. For the case of single output, K inputs, N farms, the empirical model is specified as:

$$\ln D_i = \delta + \alpha \ln Y_i + \sum_{j=1}^{4} \beta_j \ln X_{ji}, \quad i = 1,...240, \tag{4.26}$$

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 Fisher index of other inputs (seed, pesticide and herbicides). ln represents the natural logarithm of the associated variables, and δ, α and β_j are unknown parameters to be estimated.

Equation (4.26) is transformed by imposing the restriction for homogeneity of degree +1 in inputs:

$$\sum_{j=1}^{4} \beta_j = 1, \tag{4.27}$$

gives:

$$-\ln X_{ki} = \delta + \alpha \ln Y_i + \sum_{j=1}^{4-1} \beta_j \ln\left(X_{ji} / X_{ki}\right) - \ln D_i, \tag{4.28}$$

The unobservable distance term "$-\ln \mathrm{D_i}$" represents a random term and can be interpreted as the traditional stochastic frontier analysis (SFA) composed disturbance term, ε_i. Thus equation (4.28) can be rewritten as:

$$-\ln X_{ki} = \delta + \alpha \ln Y_i + \sum_{j=1}^{4-1} \beta_j \ln\left(X_{ji} / X_{ki}\right) + v_i - u_i, \tag{4.29}$$

The statistical noise (v_i) is assumed to be iid $N(0, \sigma_v{}^2)$ and independent of u_i. The selection of the distribution of u_i requires a statistical test. A likelihood ratio test was conducted to test the hypothesis that u_i is half-normally distributed $\left|N(0, \sigma_v{}^2)\right|$ against the alternative that it has a truncated normal distribution. The test could not reject the hypothesis of half-normal distribution at 5% level of significance.

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

$$T\hat{E}_i = E[\exp(-u_i) | \varepsilon_i)], \tag{4.30}$$

From the parameters of the Cobb-Douglas input distance function, the corresponding parameters of the dual cost function are analytically derived (Coelli et al., 2003) and defined as:

$$\ln C_i = b_0 + \sum_{j=1}^{4} b_j \ln W_{ji} + \phi \ln Y_i \tag{4.31}$$

where C_i is the cost of production of maize for the *i*th farmer, W_{ji} is the *j*th input price vector which includes the price of land, price of labour, price of inorganic fertilizer and implicit 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 minimisation, it can be shown that the parameters of the cost and input distance function are related as follows (Coelli et al., 2003):

$b_j = \hat{\beta}_j$, $\phi = -\hat{\alpha}$, 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:

$$\hat{X}_{ji}^{T} = X_{ji} \times T\hat{E}_i, \qquad \text{j = 1, 2, 3, 4} \tag{4.32}$$

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:

$$\hat{X}_{ji}^{C} = \frac{\partial C_i}{\partial W_{ji}} = \frac{\hat{C}_i b_j}{W_{ji}}, \quad \text{j=1, 2, 3, 4} \tag{4.33}$$

where $\hat{C}_i$ is the cost prediction obtained by substituting the estimated parameters into (the exponent) of equation (4.31). 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:

$$C\hat{E}_i = \frac{\hat{X}_i^C \cdot W_i}{X_i \cdot W_i}, \tag{4.34}$$

AE is calculated residually as:

$$A\hat{E}_i = \frac{C\hat{E}_i}{T\hat{E}_i}, \tag{4.35}$$

Each of these three efficiency measures takes a value between zero and one, with a value of one, indicating full efficiency. The model is estimated using the computer program, FRONTIER version 4.1 (Coelli, 1996a). The program gives the maximum likelihood estimates for the parameters of the model as well as the technical efficiency scores whereas a programme was written and implemented in STATA version 10.0 to compute the allocative and cost efficiency scores.

4.3.2 Non-parametric Input Distance Function

The first decision to make here is that of assumption concerning returns to scale. The VRS model permits the construction of production frontier to have increasing, constant or decreasing returns to scale and would be a desirable choice. However, the constant returns to scale model is also computed because in variable returns to scale models, the smallest and least-productive units (in terms of partial productivities) often show up as fully efficient simply because they lack peers to be compared with (Estache et al. 2004).

The DEA input-oriented CRS and VRS models are used to obtain the technical efficiency scores. The DEA model for this study is developed for the case of a single output and multiple inputs. For N farms which produce maize using K (land, labour, fertilizer and other) inputs and for the *i*th farm who produces y_i units of maize by applying x_{ji} units of kth input, the KxN input matrix, X, and the 1xN output matrix, Y, represent the data for all N farms in the sample. The input-oriented CRS DEA model is specified as:

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

$$\begin{aligned} \text{st} \quad & -y_i + Y\lambda \geq 0, \\ & \theta x_{ji} - X\lambda \geq 0, \\ & \lambda \geq 0, \end{aligned} \tag{4.36}$$

where θ is the input oriented technical efficiency measure having a value $0 \leq \theta \leq 1$. The resultant efficiency measure depicts the distance of each farm unit from the frontier. If the score is equal to one, it implies that the farmer is on the frontier. The vector λ is an Nx1 vector of weights which defines the linear combination of the peers of the *i*th farmer. $X\lambda$ and $Y\lambda$ are efficient projections on the frontier. The linear programming problem is solved N times, providing a value for each farmer in the sample.

The DEA problem in equation (4.36) has an intuitive interpretation. The problem takes the *i*th farm and then seeks to radially contract the input vector, x_i, as much as possible, while remaining within the feasible input set. The radial contraction of the input vector, x_i , produces a projected point, ($X\lambda, Y\lambda$), on the surface of the production technology. This projected point is a linear combination of these observed data points. The constraints in equation (4.36) ensure that this projected point cannot lie outside the feasible set.

The input-oriented VRS DEA model is specified as:

$$\begin{aligned} & \min_{\theta,\lambda} \theta, \\ \text{st} \quad & -y_i + Y\lambda \geq 0, \\ & \theta x_{ji} - X\lambda \geq 0, \\ & N1' \times \lambda = 1 \\ & \lambda \geq 0, \end{aligned} \tag{4.37}$$

where $N1'$ is an Nx1 vector of ones and $N1' \times \lambda = 1$ is the convexity constraint which makes the model a VRS model and it ensures that an inefficient farm is only benchmarked against farms of similar size. The linear programming problem is also solved N times, providing a value for each farmer in the sample.

The cost and allocative efficiencies are obtained by solving the following additional cost minimisation DEA problem. The cost minimising vector of input quantities for the *i*th farmer is calculated using the cost minimising CRS DEA. The model is specified as:

$$\begin{aligned}
&\min_{\lambda, x_{ji}^{C},} \; x_{ji}^{C} w_{ji} \\
&\text{st} \quad -y_i + Y\lambda \geq 0, \\
&\qquad x_{ji}^{C} - X\lambda \geq 0, \qquad\qquad (4.38) \\
&\qquad \lambda \geq 0,
\end{aligned}$$

where w_{ji} is the *j*th input price vector which includes the price of land, price of labour, price of inorganic fertilizer and price index for other inputs for the *i*th farmer and x_i^C is the cost-minimising vector of input quantities for the *i*th farmer.

Cost efficiency is calculated by dividing minimum cost by observed cost.

$$CE = \frac{w_i x_i^C}{w_i x_i} \qquad (4.39)$$

Allocative efficiency is calculated by dividing cost efficiency by technical efficiency.

$$AE = \frac{CE}{TE} \qquad (4.40)$$

where TE is the θ obtained from equation (4.36).

Under the VRS cost minimisation problem, the model in 4.38 is modified by adding the convexity constraint, $N1'\lambda = 1$ and similar procedures laid out under CRS problem are followed for computing allocative and cost efficiency.

The model is implemented using Data Envelopment Analysis Program (DEAP) version 2.1 by Coelli (1996b). The program computes all the three efficiency estimates.

4.3.3 Parametric Stochastic Frontier Production Function (SFPF)

The Cobb-Douglas model for this study is specified as:

$$\ln Y_i = \delta + \sum_{j=1}^{4} \beta_j \ln X_{ji,} + v_i - u_i \qquad (4.41)$$

All variables are as defined for the SIDF model. δ and $\beta' s$ are parameters to be estimated.

Given the vector of input prices for the ith farm (W_{ji}), parameter estimates of the stochastic frontier production function ($\hat{\beta}$) in equation (4.41), and the input oriented adjusted output level Y_i^* in equation (4.4), the corresponding Cobb-Douglas dual cost frontier is derived and written as

$$\ln C_i = b_0 + \sum_{j=1}^{4} b_j \ln W_{ji} + \phi \ln Y_i^* \qquad (4.42)$$

where $\phi = \left(\sum_{j=1}^{4} \hat{\beta}_j \right)^{-1}$, $b_j = \phi \hat{\beta}_j$, $b_0 = \frac{1}{\phi} \left(\hat{\delta} \prod \hat{\beta}_j^{\hat{\beta}_j} \right)^{-\phi}$

By using Shephard's Lemma, the cost minimising (economically efficient) input vector, X_i^C, is derived by substituting the firm's input prices and adjusted output quantity into the system of demand equations which is given as:

$$\frac{\partial C_i}{\partial W_i} = b_j W_j^{-1} C_i = X_i^C \qquad (4.43)$$

For a given level of output, the corresponding technically efficient, cost efficient and actual costs of production are equal to $W_i X_i^T$, $W_i X_i^C$ and $W_i X_i$, respectively. These three cost measures are then used as the basis for calculating the technical and cost efficiency indices for the *i*th farm:

$$TE_i = \frac{W_i X_i^T}{W_i X_i} \tag{4.44}$$

and

$$CE_i = \frac{W_i X_i^C}{W_i X_i} \tag{4.45}$$

Following Farrel (1957), allocative efficiency can be calculated by dividing economic efficiency (CE) by technical efficiency (TE):

$$AE_i = \frac{W_i X_i^C}{W_i X_i^T} \tag{4.46}$$

The model is estimated using the computer program, FRONTIER version 4.1 (Coelli, 1996a). The program gives the maximum likelihood estimates for the parameters of the model as well as the technical efficiency scores whereas a programme was written and implemented in STATA version 10.0 to compute the allocative and cost efficiency scores.

4.3.4 Technology and Policy Impact on Efficiency

To analyse the impact of technological innovation (hybrid seed, inorganic fertilizer, herbicides and conservation practices) and other policy and socioeconomic variables (gender, age, education, household size, land, off-farm work, membership in a farmer group, access to extension, credit and market) on efficiency, a second stage procedure is used whereby the efficiency scores obtained from the first stage are regressed on the selected explanatory variables using a double-bounded Tobit model. The two stage procedure is well accepted in the case of non-parametric DEA models. However, a one stage procedure would have been preferable in the case of technical efficiency in the parametric approach since the stochastic frontier is estimated under the assumption that the technical inefficiency effects are identically distributed (Battese and Coelli, 1995). However, cost and allocative efficiency in the parametric models are derived not estimated hence, a one stage procedure cannot be implemented for them. Therefore, the two stage procedure is followed in this study to ensure uniformity and consistency in the interpretation of results from all the different models. The Tobit model is implemented in STATA version 10.0. The model is specified as:

$$Y_i^* = \beta_0 + \sum_{\substack{n=1 \\ =0}}^{10} \beta_n X_{in} + \sum_{\substack{m=1 \\ =0}}^{4} \beta_m T_{im} + u_i \quad \text{if}$$

$$\left. L_i < \beta_0 + \sum_{\substack{n=1 \\ =0}}^{10} \beta_n X_{in} + \sum_{\substack{m=1 \\ =0}}^{4} \beta_m T_{im} + u_i < U_i \right\} \qquad (4.47)$$

where Y_i^* is a latent variable representing the efficiency measure for each farm household, X_i is a $nx1$ vector of explanatory variables for the ith farm, T_i is an $mx1$ vector of technology variables for the ith 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. This is because technology adoption is a decision variable and is not randomly assigned but farmers self-select themselves into it depending on a number of factors which may also have an impact on farm efficiency hence resulting in the errors in the efficiency and technology adoption models been correlated. The exogeneity of these variables were tested using the instrumental variable approach as proposed by Smith and Blundell (1986). This methodology follows two steps. In the first step, each potential endogenous variable is estimated with ordinary least squares over a set of instruments and the exogenous variables of the Tobit model. In this study, instruments are chosen according to literature on determinants of the respective technology adoption (Solis et al., 2009; Langyintuo and Mekuria 2008; Fufa and Hassan 2006; Adesina and Baidu-Forson, 1995; Adesina and Zinnah, 1993; Pike et al., 1991). The two vital features of a valid instrument are that it must be strongly related to the endogenous explanatory variable-technological innovations in our case-while at the same time it must be unrelated to the error term of the technical, allocative and cost efficiency equations. These features were put into consideration in making the choice. It is a common practice to have same instrument for all potential endogenous variables. However, for this study two instruments were found for each technology as this takes care of the specific characteristics of each technology though some instruments may also apply to more than one technology.

In the second step, the predicted residual from the OLS regression is included as an additional explanatory variable and the revised Tobit model is estimated. If the coefficient of the predicted residual is found not to be statistically significant (i.e. has no explanatory power), then the potential endogenous variable can be treated as exogenous. However, if the null hypothesis of exogeniety is rejected, then the potential endogenous variable is truly endogenous and an alternative method has to be used to correct for endogeneity. This test is related to an auxiliary regression test for exogeneity in a regression context, which in turn is a convenient alternative to the commonly employed Hausman test. To correct for endogeneity, the 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.

CHAPTER 5

STUDY AREA, SURVEY DESIGN AND SOCIO-ECONOMIC CHARACTERISTICS OF THE SAMPLE HOUSEHOLDS

5.1 Introduction

This chapter describes the study area, the research design and socioeconomic characteristics of the sample households. The next section provides the description of geographical location and agro-ecological characteristics of the study area. The description of survey design and sampling procedure is provided in section three. Section four presents data types, sources and collection. The last section provides a description of variables used for estimation of the various models and of socio-economic characteristics of sample households.

5.2 The Study Area

The study was conducted in Benue State Nigeria. Benue State whose capital city is Makurdi lies within the lower river Benue trough in the middle belt (Northcentral zone) region of Nigeria. The location of the state capital is marked with red outlined oval in figure 5.1. Its geographic coordinates are longitude 7° 47' and 10° 0' East. Latitude 6° 25' and 8° 8' North; and shares boundaries with five other states namely: Nassarawa to the north, Taraba to the east, Cross-River to the south, Enugu to the south-west and Kogi to the west. The state also shares a common boundary with the Republic of Cameroun on the south-east. Benue has a population of 4,780,389 (National Population Commission (NPC), 2006) and occupies a landmass of 32,518 square kilometers (Benue State Government, 2007).

The State is made up of 23 Local Government Areas and these are clearly shown in figure 5.1. The state comprised of several ethnic groups: Tiv, Idoma, Igede, Etulo, Abakpa, Jukun, Hausa, Akweya and Nyifon. The Tiv are the dominant ethnic group, occupying 14 local government areas, while the Idoma and Igede occupy the remaining nine local government areas. There are three agricultural zones (zones A, B, and C) in the state. Zone A Consists of Kastina-Ala, Kwande, Ukum, Vandeikya,

Figure 4.1: Map of Nigeria showing the capital cities of each State

Source: Adapted from 1992 MAGELLAN Goegraphix

Ushongo, Konshisha and Logo. Zone B consists of Gboko, Gwer East, Gwer West, Makurdi, Buruku, Guma and Tarka. Zone C consists of Ado, Oju, Agatu, Apa, Obi, Ogbadibo, Ohimini, Otukpo and Okpokwu.

Benue State experiences two distinct seasons, the wet/rainy season and the dry/summer season. The rainy season lasts from April to October with annual rainfall in the range of 100-200mm. The dry season begins in November and ends in March. Temperatures fluctuate between 23 - 37 degrees Celsius in the year. The south-eastern part of the state adjoining the Obudu-Cameroun mountain range, however, has a cooler climate similar to that of the Jos Plateau (Benue State Government, 2007).

Agriculture is the mainstay of the economy, engaging over 75 percent of the state working population. Benue State is the nations acclaimed food basket because of its rich agricultural produce which includes major crops such as yams, rice, cassava, sweet potatoes, maize, soyabeans, groundnut, sorghum, millet, beniseed and cocoyam. The state accounts for over 70 percent of Nigeria's soyabean production (Benue State Government, 2007). The major vegetation types and land use in Benue State showed that 85.6 percent of her land use is under agriculture while the remaining 10.6 percent is under forestry (Agbeja and Opii, 2005). The production and productivity trend of some of the major crops planted in Benue State is provided in table 5.1. It can be clearly observed from this table that maize productivity is very low and has remained almost static over the period. Other crops planted in the state include sugar cane, ginger, melon and beans. The state also produces large quantities of tree crops such as oil palm, cashew, coconut, oranges, banana, plantain, coffee and cola nut. Vegetables which include tomatoes, pepper, pumpkin, okro, spinach and pineapples are also produced in abundance. Benue State also possesses a great deal of livestock resources, which include goats, sheep, pigs, poultry and cattle.

Table 5.1: Production and productivity trends of major crops in Benue State

	Maize		Rice		Sorghum		Cassava		Yam	
	Output		Output		Output		Output		Output	
Year	('000MT)	Yield	('000MT)	Yield	('000MT)	Yield	('000MT)	Yield	('000MT)	Yield
2000	146.37	1.33	275.10	1.99	193.01	1.75	3526.00	13.20	2868.00	12.70
2001	148.31	1.36	275.72	2.00	191.87	1.74	3554.00	13.31	2875.00	12.72
2002	148.32	1.35	276.08	2.00	193.04	1.75	3547.00	13.28	2872.00	12.71
2003	146.42	1.34	275.90	2.00	191.52	1.74	3545.00	13.26	2871.00	12.70
2004	148.41	1.36	272.08	2.00	190.68	1.73	3548.00	13.28	2854.00	12.68
2005	148.48	1.36	274.69	2.00	191.75	1.74	3547.00	13.27	2866.00	12.70
2006	152.78	1.39	294.45	2.07	191.70	1.74	3595.61	13.29	2874.34	12.72
2007	151.05	1.38	296.15	2.07	192.94	1.75	3571.48	13.17	2872.21	12.71

Sources: Federal Ministry of Agriculture and Water resources (2008); Benue State Agricultural and Rural Development Agency (2005, 2008)

The farms are generally small and fragmented, ranging from less than one hectare to more than six hectares. Bush fallow using simple tools is the dominant system though mechanization and plantation agriculture/agroforestry are gradually creeping in. A tractor hiring unit, which specialises in land clearing and ploughing, has been established in Makurdi, the State capital. In addition, some local governments own tractors which can be hired by farmers.

The use of farm inputs, such as fertilizers, improved seed, insecticides and herbicides is on the increase through the activities of the Ministry of Agriculture, Benue State Agricultural and Rural Development Agency (BNARDA), the National Agricultural Land Development Authority (NALDA) and their network of extension workers. For instance, a total of 12563.38 metric tonnes of inorganic fertilizer, 26734.89 litres of agrochemicals and 2774.50 metric tonnes of improved seeds were used by farmers in Benue State in the 2007 agricultural production year (BNARDA, 2008). However, availability of fertiliser at affordable prices at the right time of the year and in sufficient quantity is still a big problem.

The State also boasts of one of the longest stretches of river systems in the country with great potential for a viable fishing industry, dry season farming through irrigation and for an inland water highway. The abundant agricultural potential of the state has created opportunities for investment in areas which include the following: large scale mechanized farming; post harvest processing and packaging of agricultural produce for local and external markets; vegetable oil processing; sugar processing industry; livestock farming, meat processing and marketing; fruit juice production; starch and glue production; livestock/animal feeds production; production of organic and inorganic fertilizers.

5.3 Survey Design and Sampling Procedure

Due to scarcity of resources which makes it difficult to undertake a census of all maize farmers, a sample survey was employed in this study. In drawing the sample, the laws of statistical theory of probability was followed in order to draw valid inferences from the sample and to ascertain the degree of accuracy of the results. The appropriateness of a sampling method depends on how it meets the objectives of the study successfully. A multistage sampling procedure was employed in selecting the respondents in this study.

The first stage involved a random selection of two agricultural zones since maize is produced in all the three agricultural zones in Benue State. In this stage, Zones B and C were selected. In the second stage, two Local Government Areas were purposefully selected from each zone based on the adequate representation of distinct maize production in these local government areas for the analysis of efficiency of maize production. The statistics for this selection was provided by BNARDA. Thus, in the second stage, Buruku and Gwer East were selected from Zone B while Oju and Otukpo were selected from Zone C. The third stage involved a random selection of maize farm households from the selected local government areas based on a sampling frame from Benue State Agricultural and Rural Development Agency. In each of the selected farm households, the household head who makes the day-to-day decisions on farm activities, input use and technology adoption was used as the sampling unit for this study.

Sample size determination in any study is usually a difficult task. Theoretically, the sample size is determined by the pre-assigned level of accuracy of the estimates of the mean of the parameters. Thus, knowledge of the variability of a large number of parameters is required because all have different degrees of variability. Unfortunately, this knowledge hardly exists prior to the study. Therefore, in practice sample size determination is based on consideration of financial constraints, and availability and adequacy of other resources such as time and trained manpower (Assefa, 1995 cited in Alene, 2003). However, this situation can be enhanced by stratifying the population into as many sub-population as possible based on one or more classification variables. Taking these issues into account and given that theoretically a sample size of 30 and above is considered asymptotically normal, sixty (60) maize farm households were randomly selected from each local government area, making a total of 240 farm households for the study.

5.4 Data Collection

Data was collected on all aspects that are relevant to the study. This study made use of both primary and secondary data. Given the unavailability of neither farm records by smallholders from experience nor adequate disaggregated household survey data in Benue State, a field survey method of obtaining information is adopted in this study for collecting the needed primary data. The data was collected using structured questionnaires designed for a single visit given the time and financial constraints. The questionnaire was designed in such a way that they provide adequate input-and output data and household characteristics to enable the assessment of the production efficiency of smallholder maize farmers and probable sources of any inefficiency.

To realize objectives 1 and 2, data was collected on the quantities and prices of inputs and maize output. The inputs for which data was needed for both quantities and prices were maize seeds, inorganic fertilizer, land planted to maize, family and hired labour. To realize objectives 3 and 4, data was collected on socioeconomic factors such as education, farmer experience, age, household labour force and farm size; institutional factors such as access to extension services, access to credit, access to market and membership in farmer associations; technology policy variables such as use of hybrid seeds, use of inorganic fertilizer, use of herbicides and conservation practices. In addition data was collected on farmers' perception of the attributes of the technology packages as this was needed as instruments in the preliminary analysis.

The primary data was collected with the assistance of trained enumerators. These enumerators were sourced from among the extension staff at the Benue State Agricultural and Rural Development Agency. The enumerators were trained on the survey instrument by going through the entire questions one after the other and ensuring that the intended meaning of each question is well understood. The questionnaire was pre-tested through a preliminary survey. Based on the results of the pilot survey and the trainees' field experiences, the questionnaire was modified before actual data collection was done. Further, the questionnaire was designed such that majority of the questions were closed and therefore little or no enumerator and or respondent bias is expected.

Secondary data was also obtained to supplement the primary data. Data on maize crop area, production, yield and prices were sourced from the Federal Ministry of Agriculture and Water resources, Central Bank of Nigeria, National Bureau of Statistics, State Ministry of Agriculture, and BNARDA. Also information on dissemination and use of improved maize seeds were sourced from BNARDA while information on fertilizer procurement, supply and marketing was sourced from both

BNARDA and MOA. The secondary data was essentially needed to beef up the literature on maize production trends in Nigeria in general and Benue State in particular.

5.5 Variable Description

In this section the description of all variables used for analysis is provided. The means and standard deviations of all variables used in estimation of frontier models which include the output quantity and input quantities and their respective prices are also given.

The output variable, PROD 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 man-days used by the farm household. The labour force was disaggregated by age and gender and conversion factors for adult and man equivalents were applied to arrive at the final labour used. 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. Information on inputs and output quantities in kilograms were elicited using the prevailing local measure in the study area which is a 25kg basin. For instance a farmer was asked to recall how many basins of maize he/she harvested during the last planting season and the given figures were converted to standard metrics. Likewise all area measurement was captured using the local counting in lines of crops planted. Hundred (100) lines is equivalent to a hectare. 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 following Coelli et al. 2005. All prices were in local currency, Naira.

Table 5.2 provides the summary statistics of the inputs and output used in estimation of the frontier functions and hence technical efficiency, and of input prices used in computing cost and allocative efficiency. The average production of maize is

1320.38kg. The farm size ranged between 0.4 and 2.52 with a mean of 1.2 hectares. This shows that farmers sampled for this study were actually smallholder farmers. It can easily be seen that these farmers are yet to utilize production and technology resources to a point where maximum output can be achieved and therefore is an indication of inefficiency. On average, maize farmers applied only 115.19kg of fertilizer which translates to about 95.39kg/ha. The use of fertilizer is low compared to about 400kg/ha and 600kg/ha recommended for local and hybrid maize production in the area (USAID/ICS, 2002). Labour is usually distributed between the various farm operations ranging from land preparation to harvesting. The farmers used an average of 111 man-days on their maize farms. This average includes both family and hired labour.

Table 5.2: Summary statistics of variables in the frontier functions

Variables	Mean	Standard deviation	Minimum	Maximum
Quantities				
PROD (kg)	1320.38	656.308	300.000	3780.000
LAND (ha)	1.208	0.490	0.400	2.520
LABOUR (man-days)	111.195	101.891	23.000	720.000
FERT (kg)	115.185	69.207	0.000	360.000
OTHER (index)	56.343	49.035	1.865	310.020
Prices				
WLAND (Naira)	4989.167	1726.209	3000.000	8500.000
WLABOUR (Naira)	89.808	33.675	50.000	200.000
WFERT (Naira	57.899	17.981	0.000	84.000
WOTHER (Naira)	68.638	29.938	25.537	187.696

Four variables indexing technological innovation included in second stage procedure, that is in the Tobit efficiency model are HYV, AFERT, HERB and PRACTICES. Each technology policy variable was represented by two instruments for the first stage of endogeneity-corrected Tobit model. These are YIELD and PALATABILITY for HYV. AVAILABILITY and RAINRISK for AFERT. NEED and ENVTRISK for HERB. SLOPE and DEGRADATION for PRACTICES. Other variables include AGE, GENDER, EDU, HHS, OFFWORK, MFG, EXT, CREDIT and MARKET.
The variable descriptions are given in table 5.3.

Table 5.3: Description of variables used in the second stage Tobit regression

Variable name	Description
AGE	Age of the household head in years
GENDER	1 = the household head is a male; 0 otherwise
EDU	Number of years of formal education completed by the household head
HHS	Number of persons in the household
LAND	Area of land in hectares cultivated with maize
OFFWORK	1 = engagement in off-farm work; 0 otherwise
MFG	1 = the household head is a member of any farmer organization; 0 otherwise
EXT	Number of extension visits during the cropping period
CREDIT	1 = if farmer had access to credit; 0 otherwise
MARKET	Distance to the nearest market in km
HYV	Area of maize farm (ha) cultivated with hybrid seed variety
AFERT	Area of maize farm (ha) applied with inorganic fertilizer
HERB	Area of maize farm (ha) subjected to herbicide application
PRACTICES	Number of conservation practices adopted by a farmer on his or her maize farm
YIELD	1= farmer perceives hybrid seed produces more than local variety
PALATABILITY	1= farmer perceives hybrid maize is sweeter than local maize
AVAILABILITY	1= farmer perceives fertilizer is readily available
RAINRISK	1 = farmer’s perception of poor rainfall years is low; 0 otherwise
NEED	1 = farmer perceives a need for weed control in his maize farm
ENVTRISK	1 = farmer’s perceives negative environmental effects of herbicide use
SLOPE	1 = the farmers maize farm is on a non-flat plane; 0 otherwise
DEGRADATION	1 = farmer perceives soil erosion as a problem in his or her farm.

5.6 Household and Farm Characteristics of Study Sample

Various household and farm characteristics of the farmers hypothesized to influence technical, allocative and cost efficiency of the farm households are discussed here. These include sex of the household head, age, level of formal education of the household head, household size, land holding dedicated to maize production, engagement in non-farm income generating activities, membership in a solidarity group, access to credit, access to market and access to extension services. The distribution of household and farm characteristics is presented in table 5.4.

Two hundred and thirteen (213) representing about 89 percent out of 240 household were male headed while 27 (11percent) were female headed. This is not too different from the national figure where about 83 percent of households were male headed

Table 5.4: Household and farm characteristics of the sample households

Item	Frequency	Percentage
Gender of household head:		
Male	213	88.75
Female	27	11.25
Household size (count):		
2-5	30	12.50
6-10	98	40.83
11-15	71	29.58
>15	41	17.08
Mean household size	11.742	
Age (years):		
≤30	31	12.92
31-40	51	21.25
41-50	59	24.58
51-60	58	24.17
>60	41	17.08
Mean age	47.167	
Education (years):		
No formal education	82	34.17
1- 6	14	5.83
7-12	75	31.25
>12	69	28.75
Mean education	8.433	
Land (ha):		
<0.5	9	3.75
0.5-0.99	75	31.25
1-1.49	93	38.75
1.5-1.99	49	20.42
≥2	14	5.83
Mean land	1.208	
Non-farm income activities:		
None	78	32.50
Public service	40	16.67
Trading	110	45.83
Others	12	5.00
Access to credit:		
No	207	86.25
Yes	33	13.75
Membership of farmer group:		
No	131	54.58
Yes	109	45.42
Extension contact (count):		
None	120	50.00
1-3	48	20
>3	72	30
Mean	2.546	
Distance to market (km)		
1-5	156	65.55
6-10	30	12.61
>10	52	21.84
Mean distance	6.278	

Source: Survey data

while only 17 percent were female headed (NPC, 2004). The average household size in the study area is 12 persons. Large family members are considered important asset as source of farm labour in the study area. The average age of farmers is 47 years showing that majority of the farmers are still in their productive years.

Education is considered important in determining the efficiency with which farmers use production resources because it improves the skill and entrepreneurial ability of the farmer to organize inputs for the maximum efficiency. Education level in the study area is low with an average of eight (8) years of schooling. This implies that most farmers were only able to complete their primary school. The median number of years of schooling in Nigeria was 0.2 and 3.6 for females and males, respectively as at 2003 (NPC, 2004). Land and labour usually accounts for largest share of agricultural inputs in Nigeria. Land serves as a means of survival for most rural populace. Although, Benue state is known to have vast area of land, the area cultivated with maize is very small with an average of 1.2 hectares. This may be due to fragmentation of land holdings into a wide range of crops usually cultivated by farmers in Benue State. Only 14 percent of farm households own a farm size of 2 hectares and above.

Engagement in non-farm activities is an important determinant of efficiency. While on one hand it increases the income base of the farm household thus helping them to overcome credit and insurance constraints and increase their use of industrial inputs. On the other hand, it reduces the labour available for agricultural production which may have a negative effect on efficiency. About 33 percent of farmers surveyed did not engage in any non-farm activity while the remaining 67 percent were involved in one form of non-farm activity or the other. About 86 percent of farmers had no access to production credit while only 14 percent had access to credit. This situation is very common and has been serious constraint to increased agricultural productivity in Nigeria as farmers are unable to purchase the necessary inputs at the right time and quantity. Membership in a farmer group indexes social capital and 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. In Benue State, about 45 percent of sampled farmers were a member of one form of farmer organization or cooperative or the other while 55 percent did not belong to any farmer group.

Access to extension services enhances farmers' access to information and improved technological packages and is therefore postulated to be an important determinant of efficiency. The mean number of contacts with extension agents is about three times per year with half of the sampled farmers having no access to extension services. This is somewhat startling given the wide spread of Benue State Agricultural and Rural Development Agency operations in the State. Access to market serves as a proxy for the development of road and market infrastructures in any area. On average the farmers are located about 6.3 kilometres from the nearest market.

Table 5.5: Distribution of households by use of improved technology

Technology	Frequency	Percent
Hybrid seed	190	79.17
Fertilizer	225	93.75
Herbicides	153	63.75
Conservation practices	153	63.75

The distribution of farmers by use of technological innovations is presented in table 5.5. Hybrid seeds were used by 79.17 percent of farm households. Fertilizer was used by 93.75 percent of farm households. Herbicides and conservation practices were adopted by 63.75 farm households. It was however observed that the quantities used of these technologies are suboptimal as demonstrated in the case of fertilizer which therefore constrained the intended impacts.