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TECHNOLOGICAL INNOVATION AND EFFICIENCY IN MAIZE PRODUCTION IN BENUE STATE NIGERIA: A PARAMETRIC STOCHASTIC INPUT DISTANCE FUNCTION APPROACH

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Abstract

The study evaluates the technical, allocative and cost efficiencies of maize farmers and analyses the impact of technological innovations on these efficiency measures. The investigation of farm efficiency is of vital importance from both microeconomic and macroeconomic points of view. It indicates the potentials there is to improve productivity, household welfare, overall economic growth and poverty reduction by improving efficiency. It also assists policy makers in better targeting and priority setting. Policy conclusions may vary with the approach used for analysis. A number of efficiency studies in Nigeria employed the stochastic production or cost function approach. While the former may suffer from simultaneous equation bias, the later may not be practical when there is limited input price variation among farms as is evidenced in the study area or when there is a systematic deviation from cost minimizing behaviour. This study contributes methodologically by employing a parametric stochastic input distance function approach that avoids all of these problems. Results show that there is considerable inefficiency among the maize farmers and that technological innovations have significant positive impact on efficiency. Thus there is need for further public investment in maize technology development and other policy factors expected to bring about efficiency improvement of the farmers.

Key Words: technology, efficiency, parametric, stochastic, input distance function, maize

1. Introduction

The agricultural sector in Nigeria plays a crucial role for the overall economy through its significant contributions to rural employment, food security, non-oil foreign exchange earnings, and provision of industrial raw materials for other sectors in the country. It generates employment for over 70 percent of the total labour force in Nigeria, accounts for over 70 percent of the non-oil exports and provides over 80 percent of the food needs of the country (Onwuemenyi 2008; Adegboye 2004). It contributes about 42 percent to the national GDP and this value is the highest among all the other sectors with crops accounting for 89.2 percent, livestock 6.3 percent, forestry 1.3 percent and fishery 3.2 percent of agriculture GDP and 37.5 percent, 2.6 percent 0.5 percent and 1.4 percent of total GDP respectively (CBN 2007).

Maize is one of the major staples in Nigeria and therefore is of vital concern to agricultural policy decisions. Current maize production is about 8 million tonnes and average yield is 1.5 tonnes per hectare. The average yield is low when compared to world average of 4.3 tonnes/ha and to that from other African countries such as South Africa with 2.5 tonnes/ha, Cameroon, 1.9 tonnes/ha, Ethiopia, 1.8 tonnes/ha and Kenya, 1.7 tonnes/ha (FAO 2009). There has been a growing gap between the demand for maize and its supply arising from low productivity. The stronger force of demand for maize relative to supply is evidenced in frequent rise in price of maize and therefore has great implication for the food security status and economic development of the Nigerian economy. To bridge the demand-supply gap, effort has to be channeled towards increasing its productivity. Theoretically, increasing the productivity of maize production would require either increased input use especially acreage expansion, improvement in resource use efficiency and or technological change derived from use of new technologies. Given the constant population pressure and other social and economic constraints in Nigeria, acreage expansion as a source of increased productivity has little application. Hence, the country is left with the option of improving efficiency of farmers by improving on their condition or removing existing institutional, market and socio-economic constraints and introduction of improved technologies.

For more than a decade, it was thought that adopting food import as a policy would address the nation's food shortage problem, however it has become obvious that such policy rather than bring solutions, has fuelled inflation, discouraged local production and created poverty among many farm households and helped to cause food insecurity. This therefore necessitated alternative policy actions. Consequently, speedy and extensive introduction of technological change has become one of the crucial concerns in the development of Nigeria's agriculture (IDRC 2005). Much effort has been geared towards increasing the availability and adoption of improved technologies in maize production in Nigeria both at the National and State levels. Specifically, the Federal government in 2006 initiated a programme of doubling maize production in Nigeria through promotion of improved production technologies such as fertilizer, hybrid seeds, pesticides, herbicides and better management practices. Several improved maize varieties that are drought-tolerant, low nitrogen-tolerant, Striga-tolerant, stemborer-resistant and early maturing has been deployed to address the challenge faced by resource-poor farmers in maize production.

Ascertaining the feasibility of extended technologies in terms of impact on farm households is very crucial. This study focuses on impact on efficiency of farm households. The investigation of farm efficiency is of vital importance from both microeconomic and macroeconomic points of view. It indicates the potentials there is to improve productivity, household welfare, overall economic growth and poverty reduction by improving efficiency. It also assists policy makers in better targeting and priority setting. Three efficiency measures are generally considered in the literatures namely, technical efficiency, allocative efficiency and cost efficiency. Technical efficiency measures the ability of a production unit to produce maximal output from a given a set of inputs or use the minimum feasible amount of inputs to produce a given level of output. Allocative efficiency measures the ability of a production unit to use inputs in optimal proportion given their respective prices. Economic efficiency is the product of technical and allocative efficiency and can be viewed as the ability of a production unit to a given level of output at minimum cost.

Two broad approaches are usually followed in efficiency analysis in the literatures; parametric and non-parametric approaches. The parametric approach requires specification of the underlying technology and or assumption about the distribution of the inefficiency term while the non-parametric approach neither require a specific functional form nor an assumption about the inefficiency term but rather requires solving linear programs in which an objective function envelops the observed data; then efficiency scores are derived by measuring how far an observation is positioned from the “envelope” or frontier. In the parametric approach, the production technology has basically been represented either by a production or cost function. The use of distance functions have recently begun though most of the studies are motivated by the desire to calculate technical efficiency or shadow cost prices. When technical, allocative and cost efficiency are considered simultaneously, the production frontier approach may suffer from simultaneous equation bias given that the input quantities are assumed to be the decision variables. However, the direct estimation of a cost frontier may not be practical when there is limited input price variation among farms or when there is a systematic deviation from cost minimizing behaviour. Thus, policy conclusions may vary with the approach used for analysis.

Majority of efficiency studies in Nigeria employed the stochastic production frontier approach and only very few considered technical, allocative and cost efficiencies simultaneously (Oyekale and Idjesa 2009; Adewumi and Adebayo 2008; Ajibefun 2008; Adeoti and Adeoti 2008; Amaza and Ogundari 2008, 2007; Amos 2007; Ogundari *et al*. 2006; Ogundari and Ojo, 2006; Okoruwa *et al*. 2006; Umeh and Asogwa 2005). This study contributes methodologically by employing a parametric stochastic input distance function approach that avoids the problems suffered by either the production or cost function approaches. The distance function contains the same information about technology as does the cost function but may have some advantages econometrically over the cost function if, for example, input prices are the same for firms, but input quantities vary across firms (Bauer, 1990). Specifically, this study estimates the technical, allocative and cost efficiencies of maize farmers using the parametric stochastic input distance function approach to efficiency decomposition. It further analyses the impact of technological innovations on these efficiency measures. The next section describes the theoretical model, section three describes the empirical model, section four defines the data and variables used, section five discusses estimation results, and section six is conclusion.

2. Theoretical Model

The production technology of a farm may be described using a distance function. 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. In this study, the input orientation is employed because it leads to a natural decomposition of cost efficiency into its technical and allocative components and therefore the discussion is limited to input distance function. The input distance function may be defined on the input set, $L(y)$, as

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

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, positively linearly homogenous and concave in x, and 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 (Fare *et al*., 1994, Coelli and Perelman, 1999, Arega 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. Fare *et al*., 1989; Fare *et al*., 1994, Coelli and Perelman, 1999, Arega 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, Solis *et a*l., 2009). This study employs the MLE approach given the assumptions of our inefficiency term.

3. Empirical Model

The empirical model used in this study is an extension of Coelli *et al*. (2003) input distance panel data model. The Cobb-Douglas input distance function is assumed for this study. Although the study realizes the restrictive nature of the specification but its selection is based on its self-dual nature. For the case of single output, K inputs, N farms, the model is specified as:

$$\ln D_i = \delta + \alpha \ln Y_i + \sum_{j=1}^{K} \beta_j \ln X_{ji,} i = 1....N \tag{3}$$

where Y_i is the observed output for the i-th farmer and X_{ji} = is the j-th input quantity for the i-th farmer. In represents a natural logarithm, and δ , α and β_j are unknown parameters to be estimated.

Imposing the restriction for homogeneity of degree +1 in inputs upon (3),

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

Thus, the estimating equation is obtained as:

$$-\ln X_{ki} = \delta + \alpha \ln Y_i + \sum_{j=1}^{K-1} \beta_j \ln\left(X_{ji} / X_{ki}\right) - \ln D_i , \tag{5}$$

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 (5) can be rewritten as:

$$-\ln X_{ki} = \delta + \alpha \ln Y_i + \sum_{j=1}^{K-1} \beta_j \ln\left(X_{ji} / X_{ki}\right) + \varepsilon_i, \tag{6}$$

Where

$$\varepsilon_i = v_i - u_i \tag{7}$$

That is, the distances in a distance function could be due to either statistical noise (v_i) or technical inefficiency (u_i), which is the standard SFA error structure. vi are assumed to be iid $N(0, \sigma_v{}^2)$ and independent of u_i, where u_i is independently distributed as truncations at zero of a normal variable $N(\mu_i, \sigma_u{}^2)$. A likelihood ratio test was conducted between the half-normal and truncated normal distribution, the hypothesis of half-normal distribution was rejected at 5% level of significance. Given the distributional assumptions, the values of the unknown parameters can then be estimated by the maximum likelihood method.

Following Batesse and Coelli (1995), the input-orientated technical efficiency (TE) scores can then be predicted using the conditional expectation predictor:

$$TE_i = E[\exp(-u_i)|\varepsilon_i)], \tag{8}$$

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

$$\ln C_i = b_0 + \sum_{j=1}^{K} b_j W_{ji} + a_1 \ln Y_i \tag{9}$$

where C_i is the cost of production of the i-th farmer, W_{ji} is the j-th input price, b_0, b_j and a_1 are unknown parameters which are derived from the primal function. Using the first order condition for cost minimization, it can be shown that the parameters of the cost and input distance function are related as follows:

$b_j = \beta_j$, j=1, 2,…..K,

$a_1 = -\alpha$, and

$$b_0 = -\delta - \sum_{j=1}^{K} \beta_j \text{In}(\beta_j)$$

The technical efficiency scores can be predicted using equation (8) once the parameters of the input distance function has been estimated. Then, the technically efficient input quantities can be predicted as follows:

$$\hat{X}_{ji}^{T} = X_{ji} \times T\hat{E}_i, \qquad \text{j = 1, 2,………, K,} \tag{10}$$

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:

$$\hat{X}_{ji}^{C} = \frac{\partial C_i}{\partial W_{ji}} = \frac{\hat{C}_i b_j}{W_{ji}}, \quad \text{j=1,2,…K,} \tag{11}$$

where $\hat{C}_i$ is the cost prediction obtained by substituting the estimated parameters into (the exponent) of equation (9). 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 cost efficiency (CE) scores for the i-th farmer:

$$C\hat{E}_i = \frac{\hat{X}_i^C \cdot W_i}{X_i \cdot W_i}, \qquad (12)$$

Then, following Farrell (1957), allocative efficiency was calculated residually as:

$$A\hat{E}_i = \frac{C\hat{E}_i}{T\hat{E}_i}, \qquad (13)$$

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

To analyse the impact of technological innovation 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 Tobit model since efficiency scores vary between 0 and 1.

4. Data and Variables

In the absence of a reliable household census data, a field survey was conducted using a pre-tested semi-structured questionnaire. This survey was conducted in Benue State Nigeria covering the 2008/2009 agricultural season. A multistage stratified sampling procedure was employed in selecting the respondents in this study. The first stage involved a purposeful selection of two zones out of a total of three agricultural zones in the State based on their adequate representation of distinct maize production. The second stage involves a random selection of two Local Government Areas from each zone. The third stage involves a random selection of 60 maize farm households from the selected local government areas. Fourth stage involves selection of the household head. Thus, a total of 240 farmers were interviewed.

Data on output and input quantities and prices were collected. One output variable (PROD) and four input variables (LAND, LABOUR, FERT and OTHER) were used in estimating the parametric stochastic input distance function. The output variable is the quantity of maize produced during 2008/2009 agricultural season by a farmer and is measured in kilograms. LAND is measured as the area of land in hectares cultivated with maize by a farmer in the relevant period. LABOUR is measured as the amount of both family and hired labour in mandays used by the farmer. FERT is the amount of inorganic fertilizer in kilograms used by the farmer. OTHER is an implicit quantity index of seed, herbicides and pesticides used by the farmer. Observed average price per unit of inputs used were used. LANDP is rental price of a hectare of farm land. LABOURP is price of labour per day. FERTP is price of inorganic fertilizer per kilogram. OTHERP is Price Index of seed, herbicides and pesticides. All prices were in local currency, Naira.

To provide evidence of the magnitude and direction of the impact of technological innovation and other policy variables on efficiency, a number of variables were used. Three variables indexing technological innovation included are HYVPRED (predicted values of area of maize farm cultivated with hybrid seed variety); HERBPRED (predicted values of quantities of herbicides used); FERTPRED (predicted values of inorganic fertilizer used). The predicted values were used as instrumental variables because of the endogeneity of adoption decisions. Other variables include AGE (age of the household head in years); EDU (number of years of formal education completed by the household head); HHS (number of persons in the household); OFFDUM (dummy variable equal to 1 for engagement in off-farm work); MFG (a dummy variable equal 1 if the household is a member of any farmer organization); EXTTIMES (number of extension visits during the cropping period); CREDIT (a dummy variable equal 1 if farmer had access to credit); MARKET (distance to the nearest output or input market). Summary of all variables are provided in table 1 in the appendix.

5. Estimation Results

Table 2 presents the maximum likelihood estimates of the parametric stochastic input distance function. The partial output elasticity corresponds to the negative of its estimated coefficient (Coelli and Perelman 1999). The estimated coefficient of output, is less than one in absolute terms indicating increasing returns to scale which for the the parametric stochastic input distance function (SIDF) is computed as the inverse of the negative of this value, that is 1.302. Furthermore, in order to qualify as a well-behaved model, ISDF needs to be non-decreasing in inputs and decreasing in outputs (Fare et al. 1994). Result shows that all variables are significant at 5 percent and have expected signs and therefore satisfies the required conditions for concavity and monotonicity. The estimated coefficient of land is the highest, at 0.673. This result validates our findings of land being a major expenditure component of the surveyed farmers. The estimated coefficient of 'other' is computed via the homogeneity restriction, and is found to be equal 0.025 and the least. The estimate of the variance parameter, γ, is 0.96 and significant at 5 percent implying that 96 percent 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 LLF for the OLS is 46.38 thus providing LR test statistic of 26.18 and this was significant when compared with mixed chi-square value of 7. 045 at three degrees of freedom, thus rejecting the adequacy of the OLS model in representing the data.

Table 2: Maximum likelihood estimates of the SIDF model

Variable	**Parameter**	**Coefficient**	**Standard error**
Constant	δ	4.108*	0.292
Prod	α	-0.768*	0.029
Land	β_1	0.673*	0.032
Labour	β_2	0.238*	0.040
Fertilizer	β_3	0.064*	0.028
Other[a]	β_4	0.025*	0.025
	$\sigma^2 = \sigma_u^2 + \sigma_v^2$	0.266*	0.131
	$\gamma = \sigma_u^2 / \sigma^2$	0.957*	0.037
LLF		59.48	

*indicates significance at 5% level

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

Based on the estimated parameters of the input distance function, the parameters of the corresponding dual cost function were derived and this formed the basis of computing the cost and thus allocative efficiency. Results of the efficiency scores and distribution are presented in table 3. Our findings show that the mean technical, allocative and cost efficiency is 0.84, 0.63, 0.53 respectively. This shows the maize farmers in Benue State Nigeria operates with considerable inefficiency. There is still potential to improve their farm efficiency by employing appropriate policies. Thus, this naturally leads us to seek for sources of inefficiency. The distribution shows that for technical efficiency, majority of the farmers fall in the category of 70 to 89 percent while for allocative and cost efficiency majority fall in the class of 50 to 69 percent.

Table 3: Frequency distribution and estimates of efficiency

	TE	**AE**	**CE**
<30%	0	0.42	5.83
30-49%	0	10.83	32.50
50-69%	17.08	62.50	52.08
70-89%	52.08	25.00	8.75
90-100%	30.08	1.25	1.25
Mean	0.84	0.63	0.53
Std. dev.	0.112	0.117	0.137

According to the results of second step regression presented in table 4, all the variables have the expected signs except membership of a farmer group. AGE has a positive sign and significant impact on TE, AE and CE. This variable indexes experience and thus a proxy for human capital showing that farmers with greater farming experience will have better management skills and thus higher efficiency than younger farmers. Increased farming

Table 4: Determinants of technical, allocative and cost efficiency

Variables	TE		AE		CE	
	Coeff.	**SE**	**Coeff.**	**SE**	**Coeff.**	**SE**
AGE	0.010*	0.002	0.009*	0.002	0.009*	0.002
EDU	0.002	0.002	0.000	0.002	0.000	0.002
HHS	0.017*	0.006	0.009	0.006	0.003	0.006
LAND	-0.347*	0.069	-0.244*	0.066	-0.173*	0.071
OFFDUM	-0.061*	0.025	-0.019*	0.024	-0.013	0.026
MFG	-0.195*	0.059	-0.134*	0.057	-0.089	0.060
EXTTIMES	0.001	0.003	0.001	0.003	0.002	0.003
CREDIT	0.188*	0.046	0.116*	0.044	0.064	0.047
MARKET	-0.014*	0.004	-0.011*	0.004	-0.006	0.004
HYVPRED	0.718*	0.185	0.458*	0.176	0.258	0.188
HERBPRED	0.166*	0.024	0.117*	0.023	0.099*	0.025
FERTPRED	0.001*	0.000	0.001*	0.000	0.001*	0.000
LLF	135.744		146.523		151.550	

*indicates significance at 5% level

experience may lead to better assessment of the importance and complexity of good farming decision, including efficient use of farming inputs. This result is consistent with the findings of Khai *et al.* (2008). Unfortunately, the second human capital variable, EDU was not significant though positive for all efficiency measures. This may be due to the low average (8) years of formal education, depicting a generally non-completion of junior secondary school. HHS was found to be positively and significantly related to efficiency indicating the importance of abundant labour supply especially for labour intensive farming. This could have arisen from the fact that the labour variable in our study is dominated by family labour which not only increases the technical and allocative efficiency but assists in producing maximal output at the least cost.

The variable LAND is aimed at capturing the effect of scale production on the efficiency of the farm. It is expected that increased farm size diminishes the timeliness of input use and increases the cost component of a farmer's production, thus leading to decline in technical, allocative and cost efficiency. As expected, the sign of the variable was consistently negative and significant. This finding underscores the need to make policies that favour small scale farmers especially in developing countries as they are the backbone of agricultural growth. The variable OFFDUM is included to capture the effect of off-farm work on efficiency. The variable was consistently negative but only significant for technical and allocative efficiency. This implies that farmers who engage on off-farm work are likely to be less efficient in farming as they share their time between farming and other income-generating activities. Surprisingly, MFG indexing social capital was found to be consistently negative but only significant for technical efficiency. This may be due to the inactive nature of some of these organizations and their failure to appropriately link the farmers. The variable EXTTIMES was positive as expected but never significant. A similar result was obtained by AREGA (2003). This may be due to skewed nature of extension activities in the state which favours only a handful of farmers and also the low average extension contact of 2 times during the cropping season. This calls for the need for more effective policy support for extension services. CREDIT is positive and consistently significant. This is as expected since the availability of credit loses the production constraints thus facilitating getting inputs on a timely basis and therefore increasing efficiency. MARKET which captures access to market was consistently negative though not significant for cost efficiency. This implies that the farther away a farmer is from the market, the less efficient as this might not only increase his production cost but also affect the time available for farming.

Finally, an important goal of this study is to evaluate explicitly the impact of technological innovation on efficiency of maize farmers. Our findings show that all three variables indexing technology were positive and significant with exception of HYVPRED that was not significant for CE. This result shows the role of government technology policy in enhancing

Table 5: Tobit Elasticities

Variables	TE		AE		CE	
	Coeff.	**SE**	**Coeff.**	**SE**	**Coeff.**	**SE**
AGE	0.009*	0.002	0.009*	0.002	0.009*	0.002
EDU	0.002	0.002	0.000	0.002	0.000	0.002
HHS	0.015*	0.006	0.009	0.006	0.003	0.006
LAND	-0.309*	0.069	-0.244*	0.066	-0.173*	0.071
OFFDUM	-0.054*	0.025	-0.019	0.024	-0.013	0.026
MFG	-0.174*	0.059	-0.134*	0.057	-0.089	0.060
EXTTIMES	0.001	0.003	0.001	0.003	0.002	0.003
CREDIT	0.168*	0.046	0.115*	0.044	0.064	0.047
MARKET	-0.013*	0.004	-0.011*	0.004	-0.006	0.004
HYVPRED	0.640*	0.185	0.457*	0.176	0.258	0.188
HERBPRED	0.148*	0.024	0.117*	0.023	0.099*	0.025
FERTPRED	0.001*	0.000	0.001*	0.000	0.001*	0.000

farm efficiency and therefore underscores the need for further investment into agricultural research and technology development. The tobit elasticities of the variables are presented in table 5. HYVPRED had the highest elasticity of for TE, AE, CE while fertilizer had the lowest elasticity of for all three efficiency measures. This further strengthens the need for hybrid seed improvement and diffusion in Nigeria in line with the current doubling of maize production programme of the Federal Government.

6. Conclusions

The study demonstrates the application of a single equation parametric stochastic input distance function approach in a cross-sectional framework to estimation of TE, AE & CE scores thus providing efficiency scores that are free from simultaneous equation bias. Further it provides empirical evidence of the effect of technology policy on efficiency of small scale maize farmers in Nigeria thus underscoring the need for further public investment in technology development.

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APPENDIX

Table 1: Summary statistics

Variables	Mean	Std Deviation
Output and inputs:		
PROD	1320.375	656.308
LAND	1.208	0.490
LABOUR	111.195	101.891
FERT	102.585	56.103
OTHER	39.564	40.831
Efficiency Variables		
AGE	47.167	9.396
EDU	8.433	6.142
HHS	11.742	7.229
LAND	1.208	0.490
OFFDUM	0.675	0.469
MFG	0.563	0.497
EXTTIMES	2.546	5.268
CREDIT	0.138	0.357
MARKET	6.278	6.164
HYVPRED	0.803	0.295
HERBPRED	0.876	0.858
FERTPRED	93.673	62.673