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MEASUREMENT OF THE TECHNICAL EFFICIENCY OF CROP FARMS IN THE SOUTHEASTERN REGION OF NIGERIA

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ABSTRACT

This study used a restricted translog production function to estimate the technical efficiency of 300 farms in the south-eastern part of Nigeria. We specified the stochastic parametric frontier with a composite error term. By means of maximum likelihood estimation, asymptotically consistent and efficient ML estimates were obtained together with inefficiency determinants. The empirical results show that the mean level of technical efficiency is 77 per cent, while the best farm is 98 per cent efficient. This shows that with the present technology, there is still room for a 23 per cent increase in crop production. As technical efficiency is concerned, socio-economic factors which positively affect the farm potential frontier strategies for increasing input-use productivity and efficiency are urgently needed.

JEL classification: Q12, Q16

1. Introduction

ONE way peasant farmers can achieve sustainable agricultural development is to raise the productivity of their farms by improving efficiency within the limits of the existing resource base and available technology. The factor productivity growth of input-output relations and enterprises shows that small-scale farmers operate on the frontiers of the production function.

Farrell (1957) developed the concept of technical efficiency based on the input / output relationship. He suggested a method of measuring technical efficiency by estimating the production function of firms which are fully efficient. However, a farm is said to be technically inefficient when actual or observed output from a given input mix is less than the maximum possible. Efficient use of various inputs is an important part of sustainability (Harwood, 1987), which implies either fewer inputs to produce the same level of output or higher output at the same level of inputs.

As in most developing countries, agriculture is the mainstay of the Nigerian economy and improvement in the sector has been the common concern of development stakeholders. The sector has experienced diverse structural changes in the past which have been translated into different economic indicators. According Central Bank of Nigeria statisics, between 1980 to 1985, the contribution of agriculture to GPD averaged ₦34,590.00 million naira. However, from 1986 to 1996, agricultural GDP improved, moving from ₦40,500 million naira in 1986 to ₦59,389 million in 1996. Aggregate agricultural production for the period declined, however, leading to a sharp decline in per capita real GDP in agriculture. The population has, however, continued to increase. At farm level, given the growing demand for land arising from rapid industrialization and urbanization, the trend of declining agricultural land has persisted, particularly in southeastern Nigeria, the study area. Basically, there has been a substantial decrease in productivity in the agricultural sector. Nigeria has not been able to sustain a high degree of self-sufficiency. This is essentially so as the spectre of hunger, mounting food deficits and widespread rural poverty continue to linger. The high population growth rate has led to increased per caput food demand and consumption. In response, the Nigerian government has encouraged large-scale farming, the use of more inputs, intensive farming and improved production techniques to meet the rising demand for food. However, the scope for productivity growth by using more inputs may well be limited by the fact that the gradual reduction/decrease in land will eventually cause the marginal productivity of such inputs to diminish. Therefore, productivity growth in small-scale farming should rely on improvements in technical efficiency. The measurement of the technical efficiency of farms is therefore, fundamental, as doing so will help to determine whether to improve efficiency or develop new technologies in the short run.

Farms have to use available inputs as efficiently as possible to achieve optimum crop production. Inefficient use of inputs can jeopardize food availability and security. In the light of sustainable crop production, an index of resource-use productivity measurement an constitutes important empirical investigation. This study, therefore, aims to measure farm level technical efficiency effects in a conventional way, as a ratio of the observed output to the maximum feasible output, where the latter is obtained by a stochastic production frontier. Another purpose of the study is to relate estimated technical efficiencies to social, economic, and farm management variables.

2. Theoretical/Conceptual Framework

Efficiency measurement and the procedure of maximum likelihood estimation are the basic theoretical constructs on which this study is conceptualized.

The concept of efficiency goes back to the pioneering work of Farrell (1957), who drew extensively upon the works of Debreu (1951) and Koopmans (1951) to define a simple measure of firm efficiency which could account for multiple inputs. Farrell's concept of efficiency consists of two components: technical and allocative efficiency. The combination of these two components provides a measure of total economic efficiency (overall efficiency).It is possible to measure technical efficiency using an input-conserving orientation, ie, a ratio of minimum feasible input use to observed input use, conditional on technology and observed output level. It is also possible to measure technical efficiency using an output-expanding orientation, ie, the ratio of observed output to maximum feasible output, conditional on technological and observed input usage. This study measures technical efficiency effects using the output-expanding orientation.

The measurement of efficiency has resulted in the specification of various estimation methods. According to Kalaizandonakes et al. (1992), these methods can be categorized according to:

- the specification of the frontier (ie, parametric and non-parametric);
- the way the frontier is computed (ie, through programming or statistical procedures); and
- the way deviations from the frontier are interpreted (ie, as inefficiency or as a mixture of inefficiency and statistical noise).

The parametric frontier estimation can be deterministic or stochastic and programming. With the specification of the stochastic parametric frontier, deviation from the production frontier is accounted for, not only by technical inefficiency, but also by measurement error, statistical noise and other non-systematic influences (Stevenson, 1980; Greene, 1990; Coelli, 1995). Estimation of this was independently proposed by Aigner, Lovell and Schmidt (1977) and Meeusen and Vanden Broeck (1977) and has been extended by Jondrow et al. (1982). It allows for the estimation of individual firm efficiency levels with both time variations and cross sectional data. The stochastic frontier production function is defined by:

$$Y_i = F(X_i, \beta) \exp (V_i - U_i)\ i = 1, 2, \ldots N \quad (1)$$

where:

Y is the output of i^{th} firm

X_i is the corresponding $(M \times Z)$ vector of inputs

β is a vector of unknown parameter to be estimated

$F(.)$ denotes an appropriate functional form

V is a symmetric error component that accounts for random effects and exogenous shock

$U_i \leq 0$ is a one-sided error component that measures technical inefficiency

Estimation of inefficiency effect, $-U$, from statistical noise, V, is accomplished by estimating the means of conditional distribution of U given V expressed as:

$$\left(\frac{U}{e_i}\right) = \mu_i + \sigma^* \left\{ f^* \left(-\frac{\mu_i}{\sigma^*} \right) \left[1 - F\left(\frac{\mu_i}{\sigma^*} \right) \right] \right\}^- \qquad (2)$$

where: $$\sigma^* = \left(\frac{\sigma_v^2 \sigma_u^2}{\sigma^2} \right)^{1/2} ; \mu = \frac{(-\sigma_u^2 e_i)}{\sigma^2},$$

f is the standard density function, and

F is the standard distribution function

This is done by means of maximum likelihood (ML) estimation. This involves the estimation of population parameters such that the probability density for obtaining the actual sample observations that have been obtained from the population is greater than the probability density obtainable with any other assumed values (estimations) of the population parameters (Draper and Smith, 1966 and Olayemi, 1998). The ML method provides estimators that are asymptotically consistent and efficient. This study relies upon the estimation of the stochastic frontier by the ML method.

Advances have been made in the evaluation of efficiency. Studies by Clayton (1961), Ogunfowora (1970), Abalu (1975), and Belete et al., (1993) utilized mathematical programming to estimate firm efficiency. Hopper (1965) and Ram (1980) evaluated efficiency by using the ordinary least squares method, commonly called the deterministic approach. In recent years, however, econometric modeling of stochastic frontier methodology associated with efficiency estimation has been an important area of research. These studies are mostly based on the Cobb-Douglas function and the transcendental logarithmic functions that are specified either as a production function or a cost function (see Battese and Corra, 1977; Kalirajah, 1981; Bagi, 1984; Bagi and Humpag, 1983; Kumbhakar, 1994; Ali, 1996; Apezteguia and Gerate 1977; Yao and Liu, 1998 and Reinhard et al., 1999). For all these studies, farm level technical efficiency effects ranged from 0.20 to 0.98. In Nigeria, however, the use of the stochastic frontier to estimate farm-level efficiency effects is indeed limited. This study uses a production function approach to estimate efficiency at farm level by assuming a stochastic nature of production.

3. Methodology

3.1 The study area, sampling and data collection

The study was conducted in Odukpani Local Government Area in Cross River State and Itu Local Government Area in Akwa Ibom State. The area is situated along the Calabar-Itu highway - a major road linking the two states with other states in the eastern part of the country, and lies within the rainforest ecological zone, with pockets of mangrove swamps. It is an intensive crop-growing area, basically a farm settlement. Farmers, both full-time and part-time migrate to the area for crop production, and farming activities continue throughout the year.

A two-stage sampling technique was employed in selecting the samples needed for the study. First, six villages were randomly selected along the major highway. Second, 50 farmers were selected from each village through a modified form of simple random sampling called the random walk method. Farm-level intensive cost itinerary surveys provided the basic primary quantitative and qualitative cross-sectional data from 300 sample farms, collected with the aid of structured questionnaires. The baseline survey covers information on input use, management practices, output level, crop diversity, etc.

3.2 The empirical models

A restricted translog production function was estimated in this study. The restriction was imposed so that only theoretically and economically plausible interaction terms were retained. The general form of the model is expressed as follows:

$$Q = a_0 = \sum_{i=1}^{n} a_i lnX_{ij} + \sum_{i=1}^{n} \sum_{g=1}^{n} b_{ig}(\ln X_{ij} lnX_{ij}) + \sum_{k=1}^{m} C_k D_{kj}$$

$$\sum_{=1}^{n} b_i (lnX_i)^2 + \tfrac{1}{2} \sum_{i=1}^{n} \sum_{k=1}^{m} e_i (lnX_{ii} lnXD_{kj}) + U_j + V \qquad (3)$$

where:

j = 1, 2 ..., n farms

i, g = 1, 2, ... n are physical inputs as a quantity of crop expressed in grain equivalent

X = physical inputs

D = diversification index. The diversification index is calculated using the Herfindel index represented as:

$$rop\ DI = \sum_{i=1}^{n} P_i$$

where:

P_i = proportion of the net farm income from the i^{th} crop in the combination.

U and V are as previously defined in equation 1.

$A_0, a_i, b_{ig}, C_k, b_{ij}$ and e_r are parameters of intercept, physical inputs, interaction across i^{th} and g^{th} physical inputs, diversification index, square terms of physical inputs and interaction between i^{th} physical input and diversification index respectively.

The term $U_j \leq 0$ in the above equation as it represents technical inefficiency is assumed to arise from a normal distribution with μ_j mean and variance σ^2_u, which is truncated at zero. It is further assumed that the average level of technical inefficiency, measured by the mode of the truncated normal distribution (ie, μ_j), is a function of factors believed to effect technical efficiency (Yao and Liu, 1998). In this study, estimated technical inefficiency is related to certain variables as defined in the expression below (equation 4).

$$e^{-uj} = P_0 + P_1(FS_j) + P_2(Age_j) + P_3(EDU_j) + P_4(OFW_j) + P_5(FRG_j) + P_6(MIG_j) + P_7(FMS_j) + Z_j \quad (4)$$

The values of unknown coefficients in equations (3) and (4) are jointly estimated by maximizing the likelihood function given as:

$$lnL = \frac{N}{2}\ln\left(\frac{2}{\pi}\right) - Nh\sigma + \sum_{i=1}^{n}\left[1 - F\left(\frac{-e_i\lambda}{\sigma}\right)\right] - \tfrac{1}{2}\sigma^2\sum_{i=1}^{n}\varepsilon_i^2 \quad (5)$$

where:

n is the number of observations (300)

$$= \frac{\sigma}{\sigma}$$

$F(.)$ is the standard distribution function

ε_i is the component error term

$\pi = 3.1415$

4. Results and Interpretations

4.1 ML Empirical Result and Inefficiency Model

The model specified is estimated by the maximum likelihood method using a computer programme FRONTIER 4.1 developed by Coelli (1995). The ML estimates are presented in table 1 below.

Table 1. ML Estimates of Translog Production Frontier and Inefficiency Function

Variable	Coefficient
Production Function	
Constant (a_1)	1.367 (1.805)*
Land (β_1)	0.0382 (1.8104)*
Labour (β_2)	0.6021 (2.4142)***
Other expenses (β_3)	0.00314 (0.0061)
Diversification index (β_4)	-0.8176 (8.5344)***
Land x Land (β_5)	0.1094 (2.5149)***
Labour x Labour (β_6)	0.1028 (1.6527)*
Other expenses x other expenses (β_7)	0.0219 (6.8438)***
Land x Labour (β_8)	0.5060 (4.0191)***
Land x other expense (β_9)	0.3347 (3.8604)***
Land x Diversification index (β_{10})	-0.0877 (1.2710)
Labour x Diversification index (β_{11})	0.1949 (1.2615)
Other expenses x Diversification index (β_{12})	0.2499 (2.8047)***
Inefficiency Function	
Intercept α	4.3982 (3.6726)***
Farm size (γ_1)	0.1051(3.8925)***
Age (γ_2)	0.0062 (1.2674)
Education (γ_3)	-0.008 (2.6899)***
Off-farm work (γ_4)	0.00003 (-1.32)
Fragmentation (γ_5)	0.00006 (1.89)**
Migrant Status (γ_6)	-0.2951 (-2.8650)***
Family Size (γ_7)	-0.144 (-3.78)
Diagnosis Statistics	
Sigma-square σ^2_s	0.8726 (4.9841)***
Gamma (λ)	0.9506 (2.6560)***
Ln(likelihood)	105.776
LR test	97.00

Source: Derived from Analysis

The table above shows ML estimates and inefficiency determinants of the specified frontier. The sigma square (0.8725) is large and statistically significant and different from zero at $\alpha = 0.01$. This indicates a good fit and the correctness of the specified distributed assumption of the composite error term. Moreover, the variance ratio, defined as $\lambda = \delta_u^2/\delta_u^2\delta_v^2$, is estimated to be as high as 95.06 per cent, suggesting that the systematic influences that are unexplained by the production function are the dominant sources of random errors. In other words, the existence of technical inefficiency among the sample farms accounts for about 95 per cent of the variation in the output level of the crops grown. This confirms that in the specified model, there is the presence of a one-sided error component and that a classical regression model of the production function based on the ordinary least squares estimation would be an inadequate representation of the data. The results of the diagnostic statistics therefore confirm the relevance of the stochastic parameters of the production frontier and maximum likelihood estimation. Over 76 per cent of the coefficients are statistically significant at different critical values indicating the relative importance of factor inputs in crop production. Labour appears to be the most important factor of production with an elasticity of 0.6021, showing the labour-intensive nature of farming in the study area. The sign and magnitude of the crop diversification index coefficient, -0.8176, indicate that a higher level of crop diversification is associated with decreasing output. Therefore, it is likely that the diversification practices may not be optimal in terms of different classes of crops in a mixture (see tables 3 and 4) and that the nutrient status of the land may not be adequate to support more crops per plot. Basically, the coefficients of the conventional inputs and their interaction terms are *a priori* signs and magnitude except for 'other expenses'.

The estimated coefficients of the inefficiency function provide some explanations for the relative efficiency levels among individual farms. All the efficiency variables are highly significant, except age and off-farm work. Since the dependent variable of the inefficiency function represents the mode of inefficiency, a positive sign of an estimated parameter implies that the associated variable has a negative effect on efficiency, and a negative sign indicates that the reverse is the case. Thus farm size, off-farm work and fragmentation has a negative effect on efficiency. The allocation of more time to off-farm work produces extra cash for the family, but it has a negative impact on farm activities. This is because farmers have an incentive to work elsewhere if the income they receive from off-farm work more than offsets the loss resulting from the negligence of farm activities.

On the other hand, education, migrant status and family size each have a positive impact on efficiency. These results seem plausible. Large family size ensures availability of enough labour for farm operations. More years of education enable farmers to acquire and process relevant information more effectively. This result agrees with previous works by Ram (1980); Huffman (1977) and Parikh et al. (1995).

4.2 Resource-use efficiency

Farm-specific resource use efficiency indices are shown in table 2 below:

Table 2. Distribution of Farm-Specific Technical Efficiency Indices Among Farmers

Efficiency Class (%)	Frequency	Percentage
1 - 10	2	0.67
11 - 20	2	0.67
21 -30	2	0.67
31 - 40	2	0.67
41 - 50	7	0.33
51 - 60	17	5.67
61 - 70	32	10.67
71- 80	80	28.67
81 - 90	134	44.67
91 - 100	16	5.33

Mean value	= 0.77	Maximum value	= 0.98
Mode value	= 0.84	Skewedness	= -0.50
Minimum value	= 0.01		

The results show a wide variation across farms. The minimum efficiency index is 0.01 while the maximum value is 0.98. The distribution spreads from left to right at different intervals and the modal class does not fall into any of the extreme classes. Therefore, the mode of 0.84 supports the use of a more general truncated-normal distribution, instead of the commonly assumed half normal distribution for the efficiency effect.

The rather high degree of technical efficiency suggests that very little marketable output is wasted. The inability of any farm to be on the frontier could be attributed to certain factors, ranging from technical production constraints and socio-economic factors to environmental factors. Specifically, in subsistence agriculture, scarce inputs may be allocated to various uses on the basis of their marginal shadow values thereby preventing the farmers from reaching the efficiency frontier. Furthermore, non-physical inputs like experience, information asymmetry and other socio-economic factors influence the ability of a farmer to use the available technology efficiently. When the land use and management practices of the farmers result in degradation, the frontier production level would also be affected.

4.2 Analysis of crop diversification pattern

The pattern of land use as regards planting of crops is measured using an index of crop diversification. The index is the Herfindel Index which is modelled in terms of the proportion of net income from the various crops in each combination. Table 3 shows the indices.

Table 3. Herfindel Index of Crop Diversification

Description	Frequency	Indices	S.D.	Min Value	Max Value	C.V. (%)
Sole	57	1	1	1	1	100
Two-Crop	102	0.57	0.12	0.22	0.96	21.00
Three-Crop	89	0.45	0.07	0.35	0.78	15.00
Five-Crop	43	0.40	0.09	0.22	0.71	24.00
Other Crop Patterns	9	0.35	0.13	0.18	0.60	37.00
Sample Mean	300	0.59	0.23	0.31	1	39.00

Table 3 shows that about 34 per cent of the farmers had a two-crop mixture on their field with a combination mean of diversification index being 0.57. For the three-crop combination and four-crop combination, the average H-index was 0.45 (C.V. = 0.15) and 0.40 (C.V. =0.24) respectively. This result shows that as the number of crops in a combination decreases, the H-index increases and would become one for sole cropping. However, the distribution of the indices supports the description of major crop combinations in the area of study. Table 4 reveals the major crop combination pattern in the area.

Table 4. Description of Major Crop Combinations in the Area

Combination	Frequency	Age of selected farms %	Age of total farms %
Maize-Cassava-Cocoyam	25	8.77	8.33
Cassava	41	14.39	13.67
Cassava-Cocoyam	25	8.77	8.33
Maize-Cassava	48	16.84	16.00
Maize-Cassava-Yam	21	7.37	7.00
Melon-Maize-Cassava-Okra	38	13.33	12.67
Cassava-Okra-Yam	24	8.42	8.00
Maize-Melon-Cassava	20	7.02	6.67
Maize-Cassava-Okra	23	8.07	7.67
Melon-Cassava	20	7.02	6.67
Total	285*	100	95.01

*Less the other forms of crop combination.

On the issue of crop diversity, about thirty-two (32) different types of levels of crop combinations were observed among the sampled farms. On the criteria of level of occupancy, however, only cropping patterns with a sampling fraction of 5 per cent are presented in table 4. The table shows that the cassava-maize mix was the combination most widely adopted by the farmers. Sole cassava and melon-maize-cassava-okra mix were the second and third widely adopted crop mixture. Cassava and maize, however, had the highest number of occurrences. This may not be unconnected with the easy adaptation of cassava and maize to the environment and the farmers' interest in the crops for income generation and food security.

5. Summary and Conclusion

The study centered on farm-level estimation of technical efficiency effects through stochastic parametric estimation methods. A restricted translog production frontier was estimated by maximum likelihood estimation procedure to obtain ML estimates and inefficiency determinants. The parameters obtained were asymptotically efficient and consistent. The diagnostic statistics confirmed the relevance of the stochastic function and maximum likelihood estimation; the presence of the one-sided error component; and that a classical regression model of production based on ordinary least squares estimation would be an inadequate representation of the data.

Overall, a mean technical efficiency of 77 per cent was achieved by farmers in the area showing that crop production can still be increased by 23 per cent using available technology (technique). Consequently, the estimation and identification of specific factors that affect technical efficiency is of utmost relevance for formulating strategies required to narrow the existing gap as well as increase input-use productivity.

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