Analysis of the technical efficiency of rice farms in Ijesha Land of Osun State, Nigeria

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Abstract

This study estimated technical efficiencies on rice farms in Osun State, Nigeria, and identified some socioeconomic factors, which influence productive efficiency. These technical efficiencies were estimated using the stochastic frontier production function approach applied to primary data. A translog production function was used to represent the production frontier of the rice farms. The study showed that the levels of technical efficiency ranged from 29.4% to 98.2% with a mean of 86.6%, which suggests that average rice output falls 13.4% short of the maximum possible level. Therefore in the short run there is scope to increase technical efficiencies on rice farms in the study area. The study also showed that these efficiencies are positively and significantly correlated with the application of traditional preparation methods, and with off-farm income.

1. Introduction

Rice has become a major staple in Nigeria. It is relatively easy to produce and is grown for both sale and home consumption. In some areas, there is a long tradition of rice growing, but for others, its cultivation is relatively recent.

There are many varieties of rice grown in Nigeria- some of which are considered as "traditional" varieties, while others have been introduced within the last twenty years from research institutes, or are imports from Asia. Rice is grown in paddies or on upland fields depending on the requirements of the particular variety; there is also limited mangrove cultivation.

Nigeria has experienced rapid growth in per capita rice consumption during the last three decades, from 5 kg in the 1960s to 25 kg in the late 1990s. The successive programmes launched to increase rice production have not been able to reduce the resulting rice deficit. The imposition of a ban on rice imports from 1985 to 1995, and the ensuing increase in the relative price against other major staples, boosted rice production mainly through area increase. Yields reached a plateau in the 1990s, and there is now some evidence that they are

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actually declining. In spite of the relative increase in the price of rice, per capita consumption has maintained its upward trend, showing that rice has become a structural component of Nigerian diet with a low price elasticity of demand. Rice is now an 'ordinary good' (WARDA, 2003).

Past policies did not help local rice producers secure a significant market share and imports have increase rapidly since the lifting of the ban and in spite of successive increases in the import tariff from 50% to 100%. Imported rice represents more than 20% of agricultural imports and half of the total rice consumption. Nigeria has thus become a major rice importer, second only to Indonesia over the period 1998-2002. Beyond the large volume involved, the Nigerian rice market is even more attractive than other West African markets, because Nigeria imports high-value (parboiled) rice rather than rice of lower quality typically imported into the other countries of the sub-region. WARDA in collaboration with the Nigerian Institute for Social and Economic Research (NISER) suggest a strategy to revitalize the rice sector in Nigeria. One of the key components of the strategy is increasing efficiency at producer level. This includes increasing productivity of the various rice production systems, and technology dissemination and adaptation (WARDA, 2003).

The objectives of the study are to estimate farmer – specific technical efficiencies for rice growers and identify some socio-economic factors which influence its production efficiency.

Farrell (1957) distinguishes between technical and allocative efficiency (or price efficiency) in production through the use of a "frontier" function.

Technical efficiency is the ability to produce a given level of output with a minimum quantity of inputs under a given technology. Allocative efficiency refers to the ability to choose optimal input levels for given factor prices.

Numerous studies (e.g. Obwona, 2000; Son *et al*, 1993) have attempted to determine technical efficiencies of farmers in developing countries because determining the efficiency status of farmers is important for policy purposes.

Efficiency is also an important factor in productivity growth. In an economy where resources are scarce and opportunities for new technologies are lacking, inefficiency studies will be able to show that it is possible to raise productivity by improving efficiency without increasing the resource base or developing new technology. Estimates of the extent of inefficiency also help in deciding whether to improve efficiency or to develop new technologies to raise agricultural productivity.

Shapiro (1983) concluded that government can enhance productivity among efficient farmers by emphasizing new investment or technologies, rather than extension and education efforts which are aimed at less efficient farmers. Shapiro (1983), Tadesse and Krishnamoorthy (1997), Habibullah and Ismail (1994), Son *et al* (1993) and Obwona (2000) found evidence of technical inefficiency among farmers in developing countries. Their recommendation was that government efforts would have to be directed to education, extension, social change and support. An emphasis on these activities would improve the allocation and the use of available resources so that more farmers would come closer to the efficiency level achieved by their counterparts.

2. Data

The survey was conducted in Oriade Local Government area of Osun State in Nigeria. This local government area comprises important rice growing towns such as Iwaraja, Iloko, and Erinmo-Ijesa. The study is based on cross sectional production data collected during the 2002/2003 agricultural production year in the area. Combination of purposive and random sampling was used in the survey. The choice of the study area was purposive because of the concentration of rice farmers in the area, while the selection of the rice growers in the sample was random. A structured questionnaire was used to collect relevant information from fifty randomly selected rice farmers about their socio-economic characteristics, inputs- area cultivated to rice, value of fertilizer and labour used, and output - the value of paddy rice harvested. The description of the quantitative variables is contained in Table 1.

Table 1: Summary statistics of variables

Variable	Minimum	Maximum	Mean	Standard deviation
Output	416.00	11128.00	2344.07	2.21
Land	1.20	9.00	2.60	1.71
Labour	22.00	119.00	54.12	1.37
Fertilizer	1000.00	30000.00	3420.40	2.03
Age	18.00	71.00	46.27	11.82
Experience	2.00	35.00	14.00	9.32

Source: Field survey.

3. Stochastic frontier production model

A stochastic frontier production function comprises a production function of the usual regression type with a composite disturbance term equal to the sum of two error components. (Aigner and Van de Broeck, 1977; Meeusen and Van de Broeck, 1977).

One error component represents the effect of statistical noise (e.g. weather, topography, distribution of supplies, measurement error, etc.). The other error component captures systematic influences that are unexplained by the production function and are attributed to the effect of technical inefficiency.

In this study, we used a variant of the stochastic frontier production function proposed by Battese and Coelli (1995) which builds hypothesized efficiency determinants into the inefficiency error component so that one can identify focal points for action to bring efficiency to higher levels.

The general form of the model is expressed as:

$$Q_1 = \beta_0 + \beta_1 X_1 + (V_1 - U_1) \tag{1}$$

where

Q_1 is the production (on the logarithm of the production) of the ith firm;
X_i is a Kx1 vector of (transformations of the) input quantities of the ith firm;
β is a vector of unknown parameters;

The V_i are random variables which are assumed to be iid $N(0,\delta_V^2)$ and independent of the U_i which are non-negative random variables assumed to account for technical inefficiency in production and are often assumed to be iid (N $(0, \delta_u^2)$.

It is further assumed that the average level of technical inefficiency, measured by the mode of the truncated normal distribution (i.e. U_i) is a function of factors believed to affect technical inefficiency as shown below:

$$U_i = \delta_o + \delta_i Z_i \tag{2}$$

where

Z_i is a column vector of hypothesized efficiency determinants and δ_o and δ_i are unknown parameters to be estimated.

It is clear that if U_i does not exist in equation (1) or $U_i = \delta_o^2 = 0$, the stochastic frontier production function reduces to a traditional production function. In that case, the observed units are equally efficient and residual output is solely explained by unsystematic influences. The distributional parameters, U_i and δu^2 are hence inefficiency indicators, the former indicating the average level of technical inefficiency and the latter the dispersion of the inefficiency level across observational units.

Given functional and distributional assumptions, the values of unknown coefficients in equations (1) and (2), i.e. β_s, δ_s, δ_u^2 and δ_v^2 can be obtained jointly using the maximum likelihood method (ML). An estimated value of technical efficiency for each observation can then be calculated in

$$T_{EI} = \exp(-U_i) \tag{3}$$

The unobservable value of V_{it} may be obtained from its conditional expectation given the observable value of $(V_i – U_i)$ (Yao and Liu, 1998).

4. Empirical specification

The functional form of the stochastic frontier was determined by testing the adequacy of the Cobb-Douglas (which is usually fitted and highly restrictive) to the less restrictive translog. Thus, the frontier models estimated are defined as:

$$y_i = \beta_0 + \sum_{i=1} \beta_i x_i + V_i - U_i \tag{4}$$

and

$$y_i = \beta_0 + \sum_{i=1}^{3} \beta_i x_i + \sum_{i=1}^{3} \sum_{i=1}^{3} \beta_{ij} xx_{ji} + V_i - U_i \tag{5}$$

respectively.

In these equations,

Q_i	=	Value of rice (₦)
X_i	=	Farm size (ha)
X_2	=	Labour (mandays)
X_3	=	Fertilizer (naira, Nigeria's currency, about ₦130/1.00US$)
U_i	=	Farmer-specific characteristics related to production efficiency
V_i	=	Statistical disturbance term
$\lvert U_i \rvert$	=	$\delta_0 + \delta_1 Z_1 + \delta_2 Z_2 + \delta_3 Z_3 + \delta_4 Z_4 + \delta_5 Z_5 + \delta_6 Z_6$ (6)

where

Z_1 = Age of farmer (years)
Z_2 = Farming experience (years)
Z_3 = Family size
Z_4 = Application of traditional preparations (1 –applied; 0 – not applied)
Z_5 = Extension contact (1 – contact; 0 – no contact)
Z_6 = Off-farm income (1 – off-farm income; 0 – no off-farm income)

Traditional preparations are expected to frighten birds off the farms, but not to kill them. Here quantum is not important but application or non-application is what matters. Hence, it is not a basic input for rice production in the study area and therefore not included in the production function.

The maximum likelihood estimates of the parameters in the Cobb-Douglas and translog stochastic frontier production function models defined by (4) and (5), given the specification for the technical inefficiency effects defined in (6), were obtained using FRONTIER 4.1 (Coelli, 1994). The unknown parameters of the stochastic frontier and the inefficiency effects are estimated simultaneously. Hypothesis tests based on the generalized Likelihood Ratio (LR) test were conducted to select the functional form. The null hypothesis here is that Cobb-Douglas is an adequate representation of the data. The likelihood-ratio statistic, $\lambda = -2\{\log[\text{Likelihood}(H_0)] - \log[\text{Likelihood}(H_1)]\}$ has approximately χ^2_q distribution with q equal to the number of parameters assumed to be zero in the null hypothesis. The LR test indicates that the Cobb-Douglas is rejected; indicating that the more general form of the translog fits these data better. The LR test establishes that some unknown combination of the squared and cross product terms in the translog improve the fit of the model.

Output elasticities with respect to the inputs x_i, for the translog are obtained by mean differencing all the variables (output, inputs and inefficiency variables) before estimation (Coelli *et al,* 1998). With this, the elasticities for the three inputs are the coefficients of the direct Cobb-Douglas terms, X_1, X_2 and X_3 in the mean differenced translog equation and the returns to scale coefficient, ϵ, is the sum of the elasticities of the inputs:

$$\epsilon = \Sigma\beta_i \tag{7}$$

5. Results and discussion

The ML estimates for the mean-differenced translog are presented in Table 2. The significance of the coefficient of γ at the 1% level suggests the presence of one-sided error component. This means that the effect of technical inefficiency is significant; hence the average production function is not an adequate representation of the data. The variance ratio, defined by $Y = \delta_u^2 / (\delta_u^2 + \delta_v^2)$, is estimated to be 51.3%, meaning that about 51% of the discrepancies between observed output and the frontier output are due to technical inefficiency. In other words, the shortfall of observed output from the frontier output is primarily due to factors, which are within the control of the rice growers in the sample under study.

Table 2: ML estimates of translog frontier production function

Variable	Parameter	Coefficient	t-ratio
Constant	β_0	0.177	3.784***
$\ln X_1$	β_1	0.324	2.002**
$\ln X_2$	β_2	-0.173	-0.755
$\ln X_3$	β_3	0.638	5.484***
$(\ln X_1)^2$	β_{11}	0.505	1.404
$\ln X_1 \ln X_2$	β_{12}	-0.310	-0.686
$\ln X_1 \ln X_3$	β_{13}	-0.364	-1.080
$(\ln X_2)^2$	β_{22}	-0.310	-0.983
$\ln X_2 \ln X_3$	β_{23}	0.783	2.007**
$(\ln X_3)^2$	β_{33}	0.0139	0.128
Inefficiency function			
Intercept	δ_0	0.503	1.005
Age	δ_1	-1.311	-1.608
Education	δ_2	-0.302	-0.721
Family size	δ_3	0.823	1.274
Pesticides	δ_4	-0.836	-2.862***
Extension	δ_5	0.798	2.277**
Off-farm income	δ_6	-0.486	-1.678*
Diagnosis statistics			
Sigma-square ($\delta^2 = \delta_u^2 + \delta_v^2$)		0.0615	3.397***
Gamma ($\gamma = \delta_u^2/\delta^2$)		0.513	5.038***
ln (Likelihood)		10.557	
LR test		26.675	
Average = TE		0.866	

*Significant at 10% level; **Significant at 5% level; ***Significant at 1% level

Note: A negative sign of the parameters in the inefficiency function means that the associated variable has a positive effect on technical efficiency, and vice versa.

The estimated elasticities of mean output with respect to land, labour and fertilizer inputs are 0.32, -0.17 and 0.64 respectively. This means that for a 10% increase in area cultivated to rice, rice output will increase by 3.2%. A 10% increase in the amount of fertilizer applied to rice also increases rice output by 6.4%. But a 10% increase in labour decreases rice output by 1.7%. The elasticity estimates of land and fertilizer are statistically significant at 5% and 1% levels, respectively; while that of labour is not so at all conventional levels. These results indicate the relative importance of the inputs in rice production. Fertilizer appears to be the most important factor of production, being consistent with the observation that fertilizer is not readily available at affordable prices to the rice farmers in the area of study. The policy implication is that it is imperative for the government to continue its efforts to make fertilizers available to farmers at affordable prices and on time. Land is next to fertilizer in terms of importance while labour input appears to be excessive because of the negativity of its coefficient. Using the significant coefficients only, the returns-to-scale parameter is estimated to be 0.962, implying decreasing returns to scale in the enterprise.

The results in Table 3 show the distribution of technical efficiency among the respondents. There is great variation in the levels of efficiency – the range is from 29.4% to 98.2% with a mean of 86.6%. The mean level of technical efficiency indicates that on average rice output falls 13.4% short of the maximum possible level. Therefore in the short run it is possible to increase rice production in the study area by an average of 13.4 per cent by adopting the technology used by the best performers. The majority (75.56%) of the farmers belonged to the most efficient category (90 to 100 per cent) while 6.67% belonged to the least efficient category (30 to 40 per cent).

Table 3: Distribution of farmer – specific technical efficiencies

Efficiency	Number of Farmers	Percentage
30<40	3	6.67
40<50	2	4.44
50<60	1	2.22
60<70	1	2.22
70<80	1	2.22
80<90	3	6.67
90<100	34	75.56
Total	45	100.00
Mean	86.6	---
Minimum	29.4	---
Maximum	98.2	---

The estimated coefficients for the inefficiency function provide some explanation for the relative efficiency levels among the farmers. Half of the efficiency variables are not significant, but those of pesticides, extension services and off-farm income are at the conventional levels. Thus the application of traditional preparations and off-farm income appear to have led to a higher level of efficiency. In other words, application of traditional preparations helps to reduce output loss due to birds on rice farms in the study area.

The fact that the extension variable is significant, but with an unexpected negative relationship with technical efficiency, deserves further investigation.

6. Conclusion

The results show that rice production in the study area can be increased with the current levels of inputs and technology in the short run if less efficient farms are encouraged to follow the resource utilization pattern of the most efficient farms.

The efficiency level is positively and significantly correlated with application of traditional preparations and off-farm income, but unexpectedly negatively and significantly correlated with contact with extension officers.

Following from the findings of this study, it is suggested that (i) an appropriate policy or regulation that recognizes and encourages proper and effective use of traditional preparations be formulated by state authorities at various levels; (ii) rice growers should engage in off-farm jobs and (iii) the activities of the extension agents in the study area should be investigated further.

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