STOCHASTIC PRODUCTION FUNCTIONS AND TECHNICAL EFFICIENCY OF FARMERS IN SOUTHERN MALAWI☆

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Abstract

This paper estimates production functions and technical efficiency in farming activities in southern Malawi using the stochastic frontier approach. We compute individual farm efficiencies for 136 farms that mainly grow maize, rice, groundnuts and pulses. We also attempt to identify determinants of technical efficiency of farmers under different assumptions about the one-sided error term. The results show that on average farmers are inefficient in Malawi and could increase output by using the same input levels by 47 percent, 48 percent and 32 percent assuming half-normal, truncated normal and exponential distributions of the one-sided error term, respectively. We also find that those farmers that partly used hired labour and those that applied fertilizer were more technically efficient compared with those that only used family labour and did not use fertilizers. The analysis also shows that small farms were more efficient compared with larger farms.

Key words: production functions; technical efficiency; Malawian agriculture

1. Introduction

The agricultural sector in Malawi is the main centre of economic activities accounting for 35 percent of real gross domestic product, more than 90 percent of the country's foreign exchange earnings and provides paid and self-employment to 92 percent of the population. Given the central importance of the agricultural sector in Malawi's development strategy, any inefficiency in production and deterioration in land resources pose serious consequences for sustainable economic growth and development. It is therefore important to study the level of technical efficiency in Malawian agriculture to guide policy makers on how to promote efficient production in the agriculture sector.

Several non-parametric and parametric techniques of estimating production frontiers have been developed and there is vast literature on their use to agricultural activities.[1] The concept of economic efficiency following Farrell's (1957) measure of static productive efficiency has been central to the econometric developments. Although, there are several measures of technical

[1] Some of the applications in agriculture are reviewed in Battese (1992) and Coelli (1995). Other studies include Heshmati and Mulugeta (1996), Coelli and Battese (1996), and Arnade (1998).

efficiency, we apply the stochastic production frontier approach to estimate the technical efficiency of farmers in Malawi.

In Section 2, we present the concept of technical efficiency and the stochastic production frontier approach to measurement of technical efficiency. Section 3 describes the data used in the model, definition of variables and the methods of estimating technical efficiency. Section 4 presents results on technical efficiency, and using socio-economic characteristics of farmers we attempt to identify sources of efficiency. In Section 5, we summarize the key results and provide concluding remarks.

2. Technical Efficiency and Estimation Techniques

Technical efficiency is a form of productive efficiency and is concerned with the maximization of output for a given set of resource inputs. Productive efficiency is the efficient resource input mix for any given output - the combination that minimizes the cost of producing that level of output or equivalently, the combination of inputs that for a given monetary outlay maximizes the level of production. The measures of productive efficiency are based on the 'best practice' production function proposed by Farrell (1957). Given the one output and two input framework, the efficient frontier or 'best practice' production function can be presented by the isoquant that shows the minimum combination of inputs of a given quality given the state of technology that can produce a specific level of output. Technical efficiency is measured relative to the 'best practice' frontier. Thus, points on the 'best practice' curve are efficient while those above are inefficient. With respect to the production function, points on the frontier are efficient and those below are inefficient.

Developments that followed Farrell's (1957) approach are grouped into non-parametric frontiers and parametric frontiers. Non-parametric frontiers do not impose a functional form on the production frontiers and do not make assumptions about the error term. These have used linear programming approaches and the most popular non-parametric approach has been the Data Envelopment Analysis. Parametric frontier approaches impose a functional form on the production function and make assumptions about the data. The most common functional forms include the Cobb-Douglas, Constant Elasticity of Substitution and Translog production functions. The other distinction is between deterministic and stochastic frontiers. Deterministic frontiers assume that all the deviations from the frontier are a result of firm's inefficiency while stochastic frontiers assume that part of the deviations from the frontier are due to random events (reflecting measurement errors and statistical noise) and part is due to firm specific inefficiency.[2]

The stochastic frontier approach, unlike the other parametric frontier measures, makes allowance for stochastic errors due to statistical noise or measurement errors. The stochastic frontier model decomposes the error term into a two-sided random error that captures the random effects outside the control of the firm (decision making unit) and the one-sided efficiency component. The model was first proposed by Aigner *et al.* (1977) and Meeusen and van den Broeck (1977). Assuming a Cobb-Douglas function, we define the stochastic production frontier as

$$\ln y_j = \alpha_0 + \sum_{i=1}^{m} \alpha_i \ln x_{ij} + \varepsilon_j \qquad (1)$$

where y is the level of output for the *j* th farmer, x is the value of input *i* used by farmer *j*, $\varepsilon_j = v_j - u_j$ is the composed error term, and v_j is the two-sided error term while u_j is the one-sided error term. The components of the composed error term are governed by different assumptions about their distribution. The random (symmetric) component v_j is assumed to be identically and independently distributed as $N(0,\sigma_v^2)$ and is also independent of u_j. The random error represents random variations in the economic environment facing the production units, reflecting luck, weather, machine breakdown and variable input quality; measurement errors and omitted variables from the functional form (Aigner *et al.*, 1977; Harris, 1992).

The distribution of the inefficiency component can take many forms, but is distributed asymmetrically.[3] It represents a variety of features that reflect inefficiency such as firm-specific knowledge; the will, skills, and effort of management and employees; work stoppages, material

[2] See Forsund *et al.* (1980) and Battese (1992).

[3] There is no a priori argument that suggest that one form of distribution is superior to another, although different assumptions yield different efficiency levels.

bottlenecks, and other disruptions to production.[4] Meeusen and van den Broeck (1977) and Aigner *et al*. (1977) assume that u_j has an exponential and a half-normal distribution, respectively. Both distributions have a mode of zero. Other proposed specifications of the distribution of u_j include a truncated normal distribution - $N(\mu,\sigma_u^2)$ (Stevenson, 1980) and the gamma density (Green, 1980). The stochastic model can be estimated by 'corrected' ordinary least squares (COLS) method or the maximum likelihood method. Olson *et al*. (1980) show that the COLS method performs as well as the maximum likelihood method for sample sizes below 400. We present the maximum likelihood method of estimating technical efficiency.

The maximum likelihood (ML) estimates of the production function (1) are obtained from the following log likelihood function

$$\ln L = \frac{N}{2}\ln\left(\frac{2}{\pi}\right) - N\ln\sigma + \sum_{j=1}^{N}\ln\left[1 - F\left(\frac{\varepsilon_j\lambda}{\sigma}\right)\right] - \frac{1}{2\sigma^2}\sum_{j=1}^{N}\varepsilon_j^2 \qquad (2)$$

where ε_j are residuals based on ML estimates, N is the number of observations, $F()$ is the standard normal distribution function and $\lambda = \sigma_u^2/\sigma_v^2$ and $\sigma^2 = \sigma_u^2 + \sigma_v^2$.[5] Assuming a half-normal distribution of u, following Lee and Tyler (1978) the population average technical efficiency (ATE) is measured by

$$E(e^{-u}) = 2e^{\sigma_u^2/2}[1 - F(\sigma_u)] \qquad (3)$$

where F is the standard normal distribution function. Measurement of farm level inefficiency requires the estimation of nonnegative error u. Given the assumptions on the distribution of v and u, Jondrow *et al*. (1982) show that the conditional mean of u given ε is

$$E(u_j|\varepsilon_j) = \frac{\sigma_u^2\sigma_v^2}{\sigma}\left[\frac{f(\varepsilon_j\lambda/\sigma)}{1 - F(\varepsilon_j\lambda/\sigma)} - \frac{\varepsilon_j\lambda}{\sigma}\right] \qquad (4)$$

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4 See Aigner *et al.* (1977), Lee and Tyler (1978), Page (1980) and Harris (1992).

5 Battese and Corra (1977) developed an alternative parameterization which can be estimated by a computer software FRONTIER written by Coelli (1996). The program can only accommodate half-normal and truncated normal distributions of u. The log likelihood functions are presented in Battese and Coelli (1992).

where ε_j are the residuals of the COLS or maximum likelihood estimators, $\lambda = \sigma_u^2/\sigma_v^2$ and $\sigma^2 = \sigma_u^2 + \sigma_v^2$, f and F are the standard normal density function (PDF) and the standard normal distribution function (CDF), respectively, evaluated at ε_j, λ and σ. λ is the measure of dominance of the one-sided error term u over the symmetric error v and is greater than zero. We estimate the farm level technical efficiency as

$$TE_j = \exp(-E(u_j|\varepsilon_j)) \tag{5}$$

where TE is the technical efficiency of the *j*th farm.

3. Data and Methods

The data used in this study was collected from West Malombe catchment in Mangochi Rural Development Programme in Southern Malawi.[6] The survey covered 147 farmers in the area. In this study we use 136 cases to estimate technical efficiencies, we deleted eleven cases that had zero entries on output to enable us to transform the variables into logarithms. The analysis is divided into two parts. The first part involves estimating technical efficiencies assuming a stochastic Cobb-Douglas production function specified as follows:

$$\ln(Output) = \beta_0 + \beta_1 \ln(Labour) + \beta_2 \ln(Land) + \beta_3 \ln(Capital) + v_i - u_i \tag{6}$$

where ln denotes the natural logarithm, output is the total yield of all crops in kilograms, labour is the total family labour, land is the land holding of the farmer measured in hectares, capital is the value of farm implements and other inputs including fertilizers and pesticides, and v and u are random and one-sided error terms, respectively.

Output is the value of maize, rice and other crops grown in the area in kilograms. Maize production dominates farming activities in the area and about 90 percent of total production in

[6] The data was collected for the study on land use, management and degradation ; specific methodological details and a farmer questionnaire are found in Mwafongo (1996).

the sample is maize. Labour is the size of the household. Estimating the number of hours worked on the farms from the data available was not possible. Some farmers also used hired labour, about 34.7 percent, but we could not estimate the exact amount of hired labour (Mwafongo, 1996). Thus, the estimate of family labour is highly aggregated and is likely to undermine the performance of labour in the production function.

Land is the total land holding of the household/farmer in hectares. The distribution of land in the area is highly skewed, with 73 percent of 147 farmers with land holdings of less than 2 hectares (Mwafongo, 1996). This shows that most farmers are in the smallholder sector within the intermediate farmers and net food buyer sub-groups.[7] The value of capital is the sum of the cost of farm implements, fertilizers and manure. The farming system in the area is largely subsistent and a hoe is the most common tool used in farming. Mwafongo (1996) found that about 97 percent of the farmers use a hoe as their main farm tool and less than 1.5 percent use a plough/tractor. In addition, only 49 percent of the farmers applied fertilizers, manure and pesticides in their farms.

The production frontiers are obtained by maximum likelihood method using LIMDEP Version 7.0. We assume three distributions for the one-sided error term and estimate three stochastic production frontiers: half-normal distribution of u, truncated normal distribution of u and exponential distribution of u.[8]

The second part of the analysis seeks to identify sources of efficiency using socio-economic characteristics of farmers using a censored tobit regression analysis. The following tobit regression bounded between zero and one is specified:

$$TE = f(AGE,\ EDUCATION,\ SIZE,\ HLABOUR,\ HYBRID,\ FERTILIZE) \qquad (7)$$

[7] The Malawi Government subdivides the small holder sector into three groups in terms of land holding: net food buyers, intermediate farmers and net food sellers. Net food buyers have land of less than 0.7 hectares, intermediate farmers have land of between 0.7 hectares and 1.5 hectares and the net food sellers have land of more than 1.5 hectares (Chirwa, 1998).

[8] The density functions, mean and variance and the parameters under truncated normal and exponential distribution of u are given in Green (1995). Also see Meeusen and van den Broeck (1977), Aigner *et al.* (1977), Jondrow *et al.* (1982), Corbo and de Melo (1986), Caves (1992), Mayes *et al.* (1994), Apezteguia and Garate (1997).

where TE is the measure of technical efficiency. AGE is the age of the farmer in years, EDUCATION is the level of education of the farmer in numbers of school years completed. We expect both to have a positive relationship with technical efficiency. SIZE is the relative size of the farm and enters the regression model in three category dummies. We have categorized the sample households into three groups based on land holding, namely: SMALL, MEDIUM and LARGE.[9] SMALL SIZE is the group with land holding of less than 0.7 hectares, therefore the net food buyer category. MEDIUM SIZE defines the group of intermediate farmers with land holding size of between 0.7 hectares and 1.5 hectares. LARGE SIZE defines the group of net food sellers with land holding of more than 1.5 hectares. The SIZE variable captures the scale economy effect and we expect a positive association with technical efficiency. HLABOUR is a dummy variable capturing the use of hired labour, taking a value of 1 where hired labour was used and zero otherwise. HYBRID is a dummy variable for the type of maize seeds. There are two types of maize grown in the area, local maize grown by 60 percent of the sample and hybrid maize grown by 38 percent of the sample. The dummy variable takes the value of 1 where the farmer at least used hybrid maize, and zero otherwise. This variable is of policy relevance as it relates to adoption of technology. FERTILIZE is another technology dummy variable capturing the use of fertilizers and related chemicals. The application of fertilizers in Malawi is quite low among the poor smallholder households.[10] We expect a positive relationship between technological advances and technical efficiency.

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[9] The sub-groups are based on the Malawi Government categorization of small holder farmers in terms of land holding size in Malawi (see note 7).

[10] The National Sample Survey of Agriculture, estimated that 42 percent of smallholder households, of which 31 percent and 33 percent below the 20th and 40th percentiles of income respectively, applied fertilizers (Mwafongo, 1996).

4. Empirical Results

4.1 Descriptive Statistics

Table 1 presents summary statistics for variables used in the production function and technical efficiency models. The mean output is about 2,000 kilograms but with a very high standard deviation. The lowest yield is 15 kilograms while the highest yield is about 80,000 kilograms. Few upper extreme values heavily influence the average production (skewness of 8.3 and a kurtosis of 79). For instance, as for maize production which accounts for about 90 percent of the output, Mwafongo (1996) reports that about 76 percent of 147 farmers had yields of less than 500 kilograms of maize. Family labour ranges from 1 to 13 people with a mean of 6 people.

Land is one of the critical factors of production in Malawi. The government estimated that the population density was 95 people per square kilometre. The average land holding size for the sample is 4.3 hectares and ranges from 0.05 hectare to 170 hectares with a high standard deviation of 19. This shows that the distribution of land is skewed (skewness value of 7.2 and Kurtosis value of 57). The average land per capita is 0.63 hectares showing serious land constraints in the area. The average expenditure on capital is MK360 and ranges from MK15 to an extreme value of MK30,000 (skewness of 11 and a kurtosis value of 125).

[Table 1 about here]

The average age of the farmers is 47 years and ranges from 18 years to 85 years with a standard deviation of 12 years. There are relatively older farmers in the area. The level of educational achievement in the area is quite low. Sixty-five percent of farmers in the sample never attended any school, 32 percent completed some levels of primary education and only 3 percent have secondary school education. The frequency distribution of land shows that 17 percent of farmers had small land size of less than 0.7 hectares, 47 percent had medium land size and 37 percent had large land sizes (more than 1.5 hectares). About 37 percent of farmers used hired labour, 41 percent used hybrid seeds and 50 percent applied fertilizers in their farms.

4.2 Production Functions and Technical Efficiency

The maximum likelihood estimates of the stochastic production functions under half-normal, truncated normal and exponential distributions of the one-sided error term are reported in Table 2. All the parameters have expected signs and magnitudes. The results reveal decreasing returns to scale in all the three specifications. The estimated coefficients of the production frontiers under the three assumptions about the one-sided error term are not significantly different and yield almost the same log likelihood function.

[Table 2 about here]

The estimated coefficient of labour is positive but it is statistically insignificant in all frontiers. As noted earlier, the poor performance of the labour variable in the model may be due to the high level of aggregation. Household size has been used as a proxy of family labour, which is a poor indicator and likely to understate the amount of family labour devoted to the production process.

The critical factor in the production of agricultural output in West Malombe catchment area emerges to be land. The estimated coefficient of land is positive as expected and is significant at 1 percent level in all three frontiers. The marginal contribution of land to output, *ceteris paribus*, is much higher compared with that of labour and capital. This underscores the importance of the land question in agricultural activities in Malawi. The coefficient of capital in the stochastic production frontiers is also positive and significant at 5 percent level.

Although production frontiers are similar under various assumptions about the one-sided error tern, technical indices vary across the three frontiers used in this analysis. Table 3 presents the frequency distribution and descriptive statistics of farm specific technical efficiencies. The average technical efficiency varies from 0.52 for the truncated normal distribution of the one-sided error term to 0.68 for the exponential distribution. Technical efficiency is as low as 0.13 from the half-normal or truncated normal frontiers and is as high as 0.83 from the exponential frontier.

[Table 3 about here]

The skewness also shows that the distribution of technical efficiencies based on the half-normal and truncated normal frontiers is similar. This is also clear from Figure 1. The Spearman's rank correlation is 100 percent for each pair of technical efficiencies under the three distributions, implying that there is perfect correlation of the efficiency ranks.

[Figure 1 about here]

Figure 2 also shows that the simple correlation coefficient of technical efficiencies based on the three frontiers is high. The computed Pearson correlation coefficient between technical efficiency indices obtained under the half-normal and truncated normal frontiers is 100 percent. On the other hand, the correlation coefficient between efficiency indices based on half-normal and exponential frontiers is 97.3 percent while that between the truncated normal and exponential frontier efficiency indices is 97 percent. Technical efficiency indices based on the exponential frontier are much higher for each farm compared with those obtained from the half-normal and truncated normal frontiers. Technical efficiencies based on half-normal frontier are slightly higher than those based on the truncated normal frontier.

[Figure 2 about here]

4.3 Determinants of Farm Efficiencies

Table 4 presents results of the technical efficiency model from a censored Tobit regression model based on half-normal, truncated normal and exponential frontiers. Technical efficiencies are bounded between zero and one. The estimated coefficients across the three specifications of the one-sided error term are similar, particularly those based on the half-normal and truncated normal frontiers. We find a positive relationship between farmers' age and technical efficiency, but the coefficients are highly insignificant across all the three models. Similarly, the coefficient of farmers education is statistically insignificant in all models, and is negatively associated to technical efficiency in the exponential model. There is a negative relationship between land size and technical efficiency across all the three models, suggesting that smaller farms are more efficient than large farms. Farmers in the SMALL SIZE category are significantly more efficient (at 5 percent level) compared with MEDIUM SIZE and LARGE SIZE farmers. Therefore, data do not support the scale economy argument in this study.

[Table 4 about here]

The dummy variable, HLABOUR, which represents the partial use of hired labour in the production process is positively associated with technical efficiency. The coefficient is statistically significant at 1 percent level in all the specifications. This suggests that those farmers who partly use hired labour in their farming activities in West Malombe area are more productive than those who entirely depend on family labour. The dummy variable, HYBRID that captures the use of hybrid (improved) seeds is negatively associated with technical efficiency but statistically insignificant, suggesting that yields were higher among farmers who exclusively used local maize seeds. The negative relationship may have repercussions on the appropriateness of technology. In any case, the use and productivity of hybrid seeds requires other complementary inputs such as fertilizers and proper crop management. Many smallholder farmers cannot afford such a mix of improved inputs in a land constrained farming system. Local maize seeds do not require more chemicals. Mwafongo (1996) notes that only 21 percent of the 147 farmers sold their cultivated crops for monetary gains and less than 2 percent sold their local maize while only 7 percent sold their hybrid maize.[11]

The use of fertilizers captured by the dummy variable, FERTILIZE, is positively associated with technical efficiencies and is statistically significant at 5 percent level. Thus, on average farmers who used fertilizers were more efficient than those who did not use fertilizers. The significance of fertilizers in the efficiency models has policy implications on the availability and pricing of fertilizers to smallholder farmers. Within the structural adjustment programme supported by the World Bank and IMF that began in 1981, there have been several changes in the pricing and marketing of smallholder agricultural inputs including removal of a fertilizer subsidy, liberalization of fertilizer pricing and marketing, closure of some Agricultural Development and Marketing

[11] Besides the complementary chemical and management demands of hybrid maize, local maize is favoured for subsistence for ease of its storage and low waste during milling.

Corporation (ADMARC) markets in the rural area. The policy ultimately excluded most smallholder subsistent farmers from use of farm inputs such as fertilizers.[12]

5. Conclusions

The task in this paper has been to estimate production frontiers and technical efficiencies of Malawian farmers in West Malombe catchment area. We have used the stochastic frontier approach to estimate technical efficiencies based on half-normal, truncated normal and exponential distributions of the one-sided error term. The stochastic frontiers on our data generally obtain similar production frontiers, but give different efficiency predictions with the exponential frontier predicting higher efficiency levels compared with half-normal and truncated normal frontiers. However, there is very high correlation of efficiency predictions obtained from the three stochastic frontiers and a perfect correlation in efficiency rankings.

Land emerges to be a critical factor in agricultural production in West Malombe catchment area. On average, the results show that Malawian farmers are inefficient and could increase output by at most 48 percent through appropriate use of the inputs. At individual farm level inefficiency is as high as 87 percent and as low as 17 percent. The efficiency models reveal a significant and positive relationship between technical efficiency, and use of hired labour and fertilizers. We also find that small scale farmers are more efficient compared with medium and large scale farmers. The analysis shows that farmers can increase their efficiency in production by adopting technology such as extensive use of fertilizers, and by augmenting their family labour with hired labour.

12 See Chirwa (1998), Christiansen and Stackhouse (1989).

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Table 1 Descriptive statistics

Variable	Unit of Measure	Mean	Standard Deviation	Minimum	Maximum
Frontier Variables					
Output	Kilograms	2,009	7,795	15	80,360
Labour	Persons	6	2.51	1	13
Land	Hectares	4.27	18.60	0.05	170
Capital	MK *	360	2,602	15	30,000
Farm Attributes					
AGE	Years	47	12.76	18	85
EDUCATION	Years	2	3.07	0	12
SMALL SIZE	Binary	0.1691	0.38	0	1
MEDIUM SIZE	Binary	0.4632	0.50	0	1
LARGE SIZE	Binary	0.3676	0.48	0	1
HLABOUR	Binary	0.3676	0.48	0	1
HYBRID	Binary	0.4118	0.49	0	1
FERTILIZE	Binary	0.5000	0.50	0	1

Notes: * MK = Malawi Kwacha

Table 2 Stochastic Production Frontiers

Variable	Half - Normal		Truncated Normal		Exponential	
	β	t-ratio	β	t-ratio	β	t-ratio
Constant	6.1147	10.82[a]	6.1339	3.08[a]	5.8389	12.21[a]
Labour	0.0415	0.21	0.0432	0.22	0.0451	0.23
Land	0.7395	9.08[a]	0.7391	9.10[a]	0.7398	9.00[a]
Capital	0.1731	2.18[b]	0.1725	2.16[b]	0.1721	2.20[b]
$\sigma = \sqrt{(\sigma_u^2 + \sigma_v^2)}$	1.1595	5.53[a]	1.1687	0.98		
$\lambda = \sigma_u^2 / \sigma_v^2$	1.0384	1.32	1.0754	0.91		
σ_u^2	0.6976		0.7324		0.1547	
σ_v^2	0.6469		0.6334		0.7446	
μ / σ_u			-0.0105	-0.001		
θ					2.5425	1.74[c]
σ_v					0.8629	7.19[a]
Log Likelihood	-185.55		-185.55		-185.53	

a = Significant at 1 percent b = Significant at 5 percent c = Significant at 10 percent

Table 3 Frequency Distribution of Farm Specific Technical Efficiency

Efficiency Index	Half Normal		Truncated Normal		Exponential	
	Number of Farms	Percent	Number of Farms	Percent	Number of Farms	Percent
0.00 - 0.05	0	0	0	0	0	0
0.05 - 0.10	0	0	0	0	0	0
0.10 - 0.15	1	0.74	1	0.74	0	0
0.15 - 0.20	0	0	0	0	1	0.74
0.20 - 0.25	1	0.71	1	0.74	0	0
0.25 - 0.30	3	2.21	5	3.68	0	0
0.30 - 0.35	9	6.62	11	8.09	0	0
0.35 - 0.40	8	5.88	7	5.15	1	0.74
0.40 - 0.45	10	7.35	14	10.29	1	0.74
0.45 - 0.50	26	19.12	23	16.91	4	2.94
0.50 - 0.55	11	8.09	10	7.35	7	5.15
0.55 - 0.60	22	16.18	21	15.44	9	6.62
0.60 - 0.65	20	14.71	19	13.97	16	11.76
0.65 - 0.70	9	6.62	11	8.09	28	20.59
0.70 - 0.75	14	10.29	12	8.82	29	21.32
0.75 - 0.80	2	1.47	1	0.74	27	13.85
0.80 - 0.85	0	0	0	0	13	9.56
0.85 - 0.90	0	0	0	0	0	0
0.90 - 0.95	0	0	0	0	0	0
0.95 - 1.00	0	0	0	0	0	0
All Farms	136	100.00	136	100.00	136	100.00
Statistics						
Mean	0.5313		0.5226		0.6846	
STD	0.1277		0.1317		0.1019	
Minimum	0.1381		0.1271		0.1811	
Maximum	0.7613		0.7607		0.8311	
Skewness	-0.4000		-0.4000		-1.5000	
Kurtosis	2.6000		2.5000		6.7000	

Table 4 Sources of Technical Efficiency in Malawian Farms

Variable	Half - Normal		Truncated Normal		Exponential	
	β	t-ratio	β	t-ratio	β	t-ratio
Constant	0.40300	8.26[a]	0.39006	7.75[a]	0.59213	15.17[a]
AGE	0.00106	1.26	0.00110	1.26	0.00067	1.00
EDUC	-0.00021	-0.06	-0.00025	-0.07	0.00055	0.20
SMALL SIZE	0.07356	2.27[b]	0.07558	2.26[b]	0.06006	2.32[b]
MEDIUM SIZE	0.04469	1.86[c]	0.04612	1.86[c]	0.03183	1.65[c]
HLABOUR	0.07187	3.04[a]	0.07420	3.04[a]	0.05530	2.92[a]
HYBRID	-0.02032	-0.98	-0.02074	-0.97	-0.01900	-1.15
FERTILIZE	0.05461	2.45[b]	0.05624	2.45[b]	0.04432	2.49[b]
σ	0.11752	16.49[a]	0.12118	16.49[a]	0.09395	16.49[a]
Log Likelihood	98.23		94.05		128.67	
Observations	136		136		136	

a = Significant at 1 percent b = Significant at 5 percent c = Significant at 10 percent

Figure 1 Histogram of Farm Specific Technical Efficiencies by Class

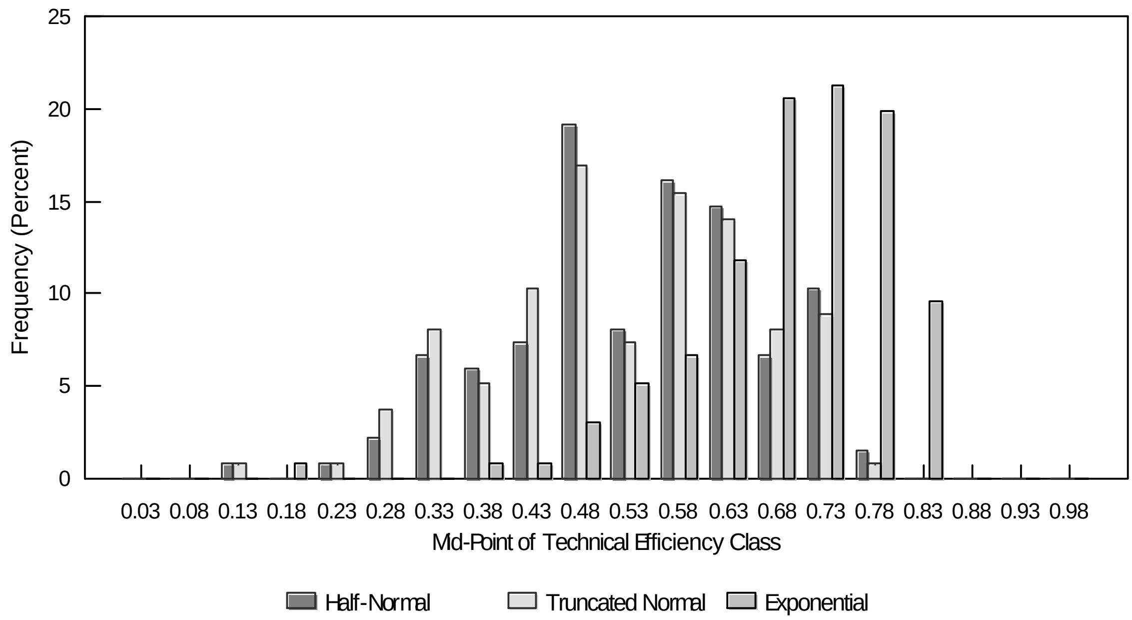

Figure 2 Farm Specific Technical Efficiencies Ranked According to Half-Normal Frontier