ESTIMATING INPUT-SPECIFIC RECOMMENDATIONS FOR TECHNICALLY INEFFICIENT CROP FARMERS

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Abstract

The main objective of this paper is to demonstrate how data envelopment analysis (DEA) and production function analysis are combined to evaluate the input usage decisions of technically inefficient maize producers and to estimate potential yield gains from reallocating inputs. The data for this research originates from a production cost survey. Two distinct quadratic production functions were estimated for DEA-determined technically efficient and inefficient farmers using a dummy variable approach. Results indicate that the yield gains are large if farmers are able to produce in a technically efficient manner while maintaining current input levels. Results further indicate that even though a producer may be technically inefficient, yield gains and therefore increased profits are possible if such farmers adjust nitrogen application rates. The conclusion is that failure to recognise the fact that DEA-determined technically efficient and inefficient producers' production processes are characterised by two distinct production functions renders uniform input recommendations inappropriate. In future, extension officers should aim to develop input recommendations taking these inefficiencies into account.

Keywords: technical efficiency, input recommendations, production functions, data envelopment analysis

Introduction

According to Coelli (1996) modern efficiency measurement began with the work of Farrell (1957) who defines technical and allocative efficiency as two important concepts of economic efficiency. Technical efficiency (TE) reflects the ability of the farm to produce a certain level of outputs with minimal inputs, whereas allocative efficiency (AE) refers to the ability of the farm to choose optimal combinations of inputs given their respective prices. One needs to be technically efficient before one can be allocatively efficient, and attainment of both technical efficiency and allocative efficiency is required for economic efficiency.

Central tendency measures have been used for many years to identify and estimate inefficiencies in the performance of decision-making units (DMUs). According to Bardhan et al. (1998), Feldstein (1974) was one of the first to use ordinary least square (OLS) regression to evaluate efficiency by estimating a production function. A DMU is classified as efficient if its observed output is higher than the estimated output from the regression, and inefficient if it is lower. Within a South African context Joubert and Viljoen (1974) used a Cobb-Douglas function to determine the relationship between production cost and technical efficiency. Viljoen and Groenewald (1977) also used a cross-sectional Cobb-Douglas production function to distinguish between different levels of efficiency within a homogeneous set of DMUs. However, advances in analytical approaches such as stochastic frontier analysis (SFA) and data envelopment analysis (DEA) have reoriented the evaluation of DMUs away from average or central tendency approaches toward best practice or frontier approaches.

Recently Mushunje et al. (2005) explained the differences in technical efficiency between cotton farmers on communal land and those on resettled land in Zimbabwe using a Cobb-Douglas-type stochastic production frontier model. Other researchers have used regression analyses to explain technical efficiency scores calculated with DEA (Galanopoulos et al., 2006). In most of the literature in which DEA is applied, researchers seek to measure the efficiency of DMUs and to explain the estimated technical efficiency (TE) scores using socio-economic and other production variables (e.g. Charnes et al., 1978; Galanopoulos et al., 2006). Some researchers also use TE scores to try and explain observed performance of DMUs (Zaibet et al., 2004).

Most early studies on technical efficiency concentrated on explaining the inefficiencies through the use of regression analysis. Although these studies were able to explain the inefficiencies, they were unable to determine specific sources and amounts of inefficiency attributed to input use. In the literature there is evidence of frustration with the failure to provide quantitative information to guide decisions on reallocation of input use in most efficiency studies, for example that of Bowlin (1998). By implication, agricultural advisors are therefore unable to make input-use recommendations to a technically inefficient farmer or to estimate potential yield gains if such a farmer were to become technically efficient. The main objective of this paper is to demonstrate how DEA and production function analysis can be combined to evaluate the input use decisions of technically inefficient maize producers in South Africa and to estimate potential yield gains from improvement in technical efficiency. The above objective is achieved using a procedure proposed by Bardhan et al. (1998), which combines DEA and OLS in a two-stage manner to estimate sources and amounts of input-specific inefficiencies.

The rest of this paper is structured as follows: In section 2 the data used in the study is discussed, while section 3 gives an outline of the linear programming and econometric models, as well as the procedure for estimating yield gains when a DMU increases its technical efficiency. Section 4 presents the results of the analyses, while section 5 provides a summary and conclusion.

Data

The data for this research originates from a production cost survey of white-maize producers in the Bothaville, Wesselsbron and Viljoenskroon areas in the Free State Province of South Africa (Le Clus et al., 2004). The farmers in this area are cash-crop producers but focus on maize production, as other crops are precluded by certain factors (e.g. product prices). The production cost survey covered 62 producers, but due to shortcomings in the data it was possible to extract a complete dataset for only 24 farmers in terms of crop yield, fertiliser applications, tractor size, and seeding rates on a per-hectare basis. However, seed (plant density) was not included in the analysis due to cultivar differences. Fertiliser applications were standardised on a mineral N basis, measured in kilograms per hectare (kg/ha), while tractor size, in kilowatts (kW), was measured as average tractor size per area of maize planted. Tractor size utilisation is a proxy for timeliness in carrying out critical operations such as planting, which indicates whether tractors are used effectively during the production process. Thus, by using tractors more intensively, farmers can increase the area of land cultivated, but have to work longer hours during the land preparation and planting stages of the production process so that planting is completed by the onset of the rainy season to ensure an increase in tractor productivity. Data on soil tests was not available, and as a result the study did not account for any nitrogen already in the soil. Weather, crop rotation, production method and labour were also not taken into consideration in the analyses, as the relevant data was not available. Table 1 shows the input use and maize yield for the total sample, as well as the DEA-determined technically efficient and inefficient sub-groups of farmers.

Table 1: Summary statistics on input use and maize yield for DEA-determined technically efficient and inefficient farmers in the Bothaville, Wesselsbron and Viljoenskroon areas

	Average	Minimum	Maximum	Standard deviation
All farmers (n = 24)				
Area planted (ha)	831	120	2369	661
Yield (ton/ha)	4.00	1.50	5.70	0.92
Tractor size utilisation (kW/ha)	14.58	2.63	50.00	10.93
Nitrogen (kg/ha)	71.20	29.83	107.27	20.15
Efficient (n_1 = 8)				
Area planted (ha)	1411*	312	2369	825
Yield (ton/ha)	4.08	2.90	5.70	1.00
Tractor size utilisation (kW/ha)	7.82*	2.63	17.95	5.41
Nitrogen (kg/ha)	65.84	29.83	99.45	23.15
Inefficient (n_2 = 16)				
Area planted (ha)	540*	120	1100	290
Yield (ton/ha)	3.90	1.50	5.10	0.91
Tractor size utilisation (kW/ha)	17.96*	6.91	50.00	11.53
Nitrogen (kg/ha)	73.88	42.12	107.27	19.19

* H0: $\mu 1=\mu 2$, Rejected at a 5% level

The average area cultivated by maize farmers can be seen in Table 1 as 831 ha. Efficient farmers cultivate 1141 ha, which is significantly ($p<0.05$) more than that cultivated by inefficient farmers, i.e. 540 ha. On average 71.2 kg of nitrogen and 14.58 kW per cultivated hectare are used to achieve a crop yield of 4 t/ha. DEA-determined technically efficient farmers achieve the same crop yields (4.08 t/ha) as the sample average. However, the DEA-efficient farmer uses 5.36 kg less nitrogen fertiliser, while the tractor size utilisation factor is 6.67 kW lower than the average of all the sample farmers. On the other hand, DEA-determined technically inefficient farmers achieve more or less the same crop yield (3.9 t/ha) as the average for all farmers, but utilise higher input amounts. On average, DEA-inefficient farmers use 2.68 kg more nitrogen, while the tractor size utilisation factor is 3.38 kW more. There is a significant difference ($p<0.05$) between DEA-determined inefficient and efficient farmers in respect of tractor utilisation. The lower tractor utilisation factor for the DEA-efficient farmers implies that these farmers cultivate larger areas per average tractor size than DEA-inefficient farmers.

Procedures

Classification of DEA-determined technically efficient and inefficient farmers

The dual formulation of the mathematical programming model proposed by Banker et al. (1984) is used to derive the efficiency frontier under conditions of variable returns to scale. Following Kalvelagen (2002) the specification of the model is:

$$\min_{\lambda,z} z = \Theta_j , \quad j = 1,2,\ldots J \qquad (1)$$

subject to $$\sum_{j=1}^{J} \lambda_j y_{kj} \geq y_{kj} , \quad k = 1, 2, ..K \qquad (2)$$

$$\Theta_j x_{ij} \geq \sum_j \lambda_j x_{ij} \;\;, \;\; \mathrm{I} = 1, 2, \ldots \mathrm{I} \qquad (3)$$

$$\sum_{j=1}^{J} \lambda_j = 1 \qquad (4)$$

For the above model it is assumed that there are J DMUs each producing K outputs using I inputs, such that y_{kj} represents the amount of the k^{th} output produced by the j^{th} DMU, and x_{ij} represents the amount of the i^{th} input used by the j^{th} DMU. z is the measure of technical efficiency and equals the ratio of the minimal feasible input usage to the current input usage and therefore Θ_j is the relative efficiency score for the j^{th} DMU. λ_j are the weights to be used as multipliers for the input levels of the referent DMU to indicate the input use level for which an inefficient farm should aim in order to achieve efficiency. The model specification requires that optimisation be carried out DMU by DMU.

The assumption of constant returns to scale means that farmers are able to linearly scale inputs and outputs without increasing or decreasing efficiency. However, this assumption only holds if the farm operates at an optimal size. Factors such as imperfect competition, constraints on finance, etc. can result in a farm not operating at optimal scale (Cinemre et al., 2005). This study assumes variable returns to scale, as the market under which a farmer operates is not perfect.

GAMS (Brooke et al., 1998) was used to develop code to optimise each DMU's efficiency score within a loop. The optimised TE scores indicate that eight farmers (33%) defined the efficiency frontier. The efficiency of the DEA-determined technically inefficient farmers ranged from 54%-89% with an average of 74%.

In order to make input recommendations and to calculate yield gains, production functions were needed for the DEA-determined efficient and inefficient farmers. The following section describes the procedure used to estimate these functions.

Estimation of production functions

Both a Cobb-Douglas and a quadratic production function were explored as the functional forms to characterise the production process. However, the Cobb-Douglas form was dropped in favour of the mixed linear quadratic form due to statistical significance. Problems with degrees of freedom may occur, because only eight farmers were DEA efficient. To overcome the problem, production functions for both groups of DMUs were estimated simultaneously using a dummy variable approach (Bardhan et al., 1998). More specifically, the following function was estimated:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_2^2 + \delta_0 D + \delta_1 D x_1 + \delta_2 D x_2 + \delta_3 D x_2^2 \qquad (5)$$

where x_1 is kilowatts, x_2 is mineral nitrogen and D is a dummy variable indicating DEA-determined technically efficient DMUs (D=1). The symbols β_0, β_1, β_2, and β_3 are the estimated coefficients for DEA-determined technically inefficient DMUs, whereas the symbols δ_0, δ_1, δ_2 and δ_3 estimate changes to the β parameters due to efficiency differences between the two groups of farmers. One benefit of using interaction terms (dummy variable interacting with inputs) is that it allows one to test whether there is a significant difference in the estimated production functions for DEA-determined technically efficient and inefficient farmers.

Calculation of gains to DMU

Using the estimated production functions it is possible to calculate the expected yield gains available to DEA-inefficient farmers. These gains may stem from two sources: Firstly, yields may improve at current input levels if DEA-determined technically inefficient DMUs are able to become technically efficient (movement to DEA-efficient production function). Secondly, DEA-inefficient DMUs may gain through changes in input levels while remaining on the inefficient production function (movement along DEA-inefficient production function).

Gains from moving to DEA-efficient production function

The following equation is used to estimate the potential yield gains of farmers moving towards the DEA-efficient production function at current input combination (Bardham et al., 1998):

$$E\left(\sum_{i=1}^{n} y(x_{1i}, x_{2i}, x_{2i}^2) \middle| D = 1\right) - E\left(\sum_{i=1}^{n} y(x_{1i}, x_{2i}, x_{2i}^2) \middle| D = 0\right) \qquad (6)$$
$$= \delta_0 + \delta_1 x_1 + \delta_2 x_2 + \delta_3 x_2^2$$

The δ_1 term represents the average increase in yield associated with the first input, while the δ_2 term represents the average increase associated with the second input, and the δ_3 term represents the quadratic form of the second input. The δ_0 term records the expected average gains from using both inputs in non-zero amounts. Note that δ refers to the estimated changes in the β parameters of the DEA-inefficient production functions. Thus, if δ parameters are not significant, only one production function is estimated and no yield gains are possible.

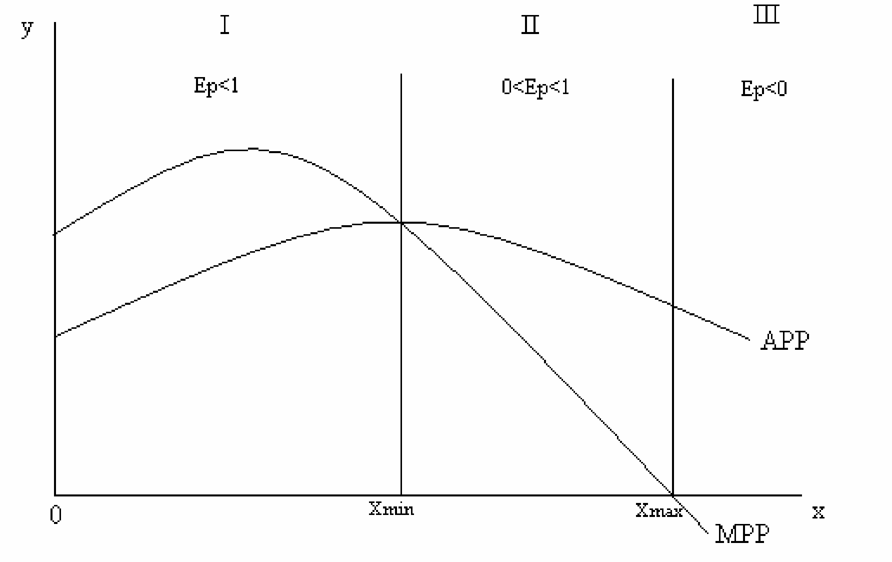
Gains from changing input combinations on the DEA-inefficient production function

Standard production economic theory is used to guide changes in input use when inefficient DMUs are unable to enhance their efficiency through a movement to the DEA-efficient production function.

Figure 1 shows the average physical product (APP), marginal physical product (MPP), and the stages of production. Stage I of production is irrational, because APP is increasing. Furthermore, MPP is greater than APP and as a result the elasticity of production (E_P) is greater than one. Production in stage III is also irrational because MPP<0, which implies that yield starts to decrease. Without any price information it is rational to increase input use to at least the beginning of stage II of production (x^{min}). On the other hand, if excessive input quantities are used, input use should be reduced to the end of stage II of production (x^{max}). Any level of input use between x^{min} and x^{max} is technically rationed. To determine the specific level of input within the range of x^{min} and x^{max}, price information is necessary.

The calculated E_P with respect to all inputs indicates that tractor utilisation for all DMUs occurs in stage II of production. For the DEA-efficient DMUs, nitrogen use also occurs in stage II, but for the DEA-inefficient DMUs, nitrogen use for production occurs in stages I, II and III. Fifty percent of the DEA-inefficient DMUs use nitrogen in accordance with stage I (E_P <1), while 25% use nitrogen in accordance with stage II (0< E_P <1) and the last 25% use nitrogen in accordance with stage III (E_P <0). The gains to DMUs producing in stage I were calculated by increasing input use for each DMU to x^{min}. On the other hand the gains for DMUs producing in stage III were calculated by decreasing input use to x^{max}.

Figure 1: Graphical representation of the stages of production using average physical product (APP) and marginal physical product (MPP)



Results

Estimated production functions for DEA-determined technically efficient and inefficient farmers

The estimated production function for both the DEA-efficient and the DEA-inefficient farmers is shown in Table 2. The estimated coefficients show that there are significant differences between DEA-efficient and DEA-inefficient farmers. In essence two separate production functions exist – one for DEA-efficient farmers and another for DEA-inefficient farmers. Both sets of farmers need to use inputs in non-zero amounts to realise an output. All the coefficients for the inefficient production function are significant at a 1% level with the exception of tractor size utilisation, which is significant at a 10% level. Changes to the production function coefficients due to improvements in efficiency are all significant at a 5% level.

Table 2: OLS estimates of the coefficients of production function

		Coefficient	**Standard error**	**t-stat**
Intercept	(β_0)	-8.765	2.189	-4.004*
Tractor size utilisation	(β_1)	0.023	0.012	1.866***
Nitrogen	(β_2)	0.303	0.056	5.378*
Nitrogen^2	(β_3)	-0.002	0.000	-4.878*
Dummy (DEA-efficient farmers)	(δ_0)	6.903	2.814	2.453**
D_Tractor size utilisation	(δ_1)	0.112	0.043	2.612**
D_Nitrogen	(δ_2)	-0.193	0.076	-2.541**
D_Nitrogen^2	(δ_3)	0.001	0.001	2.429**
R^2			0.804	
Adjusted R^2			0.718	
F-Statistics				9.379*

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

The relationship between crop yield and the tractor utilisation factor is linear and positive. The estimated values indicate that the rate at which the tractor utilisation factor contributes to yield is 0.112 units higher for the technically efficient farmers. Thus, if a DEA-efficient farmer were to increase the tractor size or decrease the area over which a tractor is used, the increase in yield would be greater than if a DEA-inefficient farmer were to increase the tractor size or decrease the area planted in the same manner.

What is interesting to note is that the rate at which nitrogen is transformed into crop yield is significantly lower (-0.193) for the DEA-efficient farmers. In addition, an estimated coefficient of 0.001 for the squared nitrogen term indicates that the production function has a lower curvature (i.e. the rate at which the production function turns as more nitrogen is applied is slower) than that for the DEA-inefficient farmers. Furthermore, the differences in the intercept term suggest that there might be other factors that could help explain the differences between DEA-efficient and DEA-inefficient farmers. The values of the coefficients β_0 and δ_0 suggest that the DEA-inefficient production function lies below the production function of the DEA-determined technically efficient farmers. In addition, the estimated coefficients also suggest that the production function associated with the DEA-efficient farmers is flatter than that of the DEA-inefficient farmers. Looking at the partial productivity of the inputs, the marginal productivity of nitrogen is lower for DEA-efficient farmers compared to DEA-inefficient farmers. One possible explanation for this might be that only a portion of the production function is estimated. For instance, if all the efficient farmers are producing in the second phase of production, the estimated coefficients will characterise the technical transformation of inputs in that phase.

Estimated gains available to farmers

Table 3 shows the yield gains from becoming DEA efficient (movement to efficient production function) and from changing the level of input use (movement along the inefficient production function). Farmers who are able to increase their efficiency by moving to the higher DEA-efficient production function stand to receive relatively large gains.

The calculated average yield gains indicate that maize yield would increase by 1.92 t/ha if the DMU were to become DEA efficient. Some of the indicated gains in Table 3 are unrealistic (DMU 6 and DMU 8). This can be the result of a random shock that occurred during the year under consideration that was not taken into account during estimation of the production function. If the farmer is unable to move to the higher DEA-efficient production function due to some factor like incomplete information or inability to acquire better technology, the farmer should at least aim to move into the rational stage of production ($0< E_P <1$).

Among the DEA-inefficient farmers, eight operate in stage I of production and should increase nitrogen application. The average amount of nitrogen that should be added to current input use levels is 10.79 kg/ha, which would result in a yield increase of 0.95 t/ha. Four DMUs are using input up to stage III of production and these DMUs would therefore gain by reducing input use levels. On average, 15.8 kg/ha less nitrogen should be applied, which would result in average yield gains of 0.41 t/ha.

Table 3: Yield gains for inefficient farmers resulting from change in technical efficiency (movement to efficient production function) and from a changing level of input use (movement along the inefficient production function)

	Technical efficiency change (moving to higher production function)	Movement along the production function			
		Changes in input amounts and crop yields			
		From stage I to II		From stage III to II	
Respondent	Yield gains	Nitrogen	Yield	Nitrogen	Yield
	t/ha	kg/ha	t/ha	kg/ha	t/ha
1	0.63	4.09	0.27		
2	1.56	5.25	0.35		
3	0.63	5.00	0.34		
4	1.38	8.51	0.62		
5	0.96	9.60	0.72		
6	5.82	13.11	1.25		
7	1.83	13.90	1.15		
8	4.23	26.88	2.93		
9	1.45			-21.27	0.75
10	1.26			-18.06	0.53
11	2.71			-13.67	0.30
12	0.59			-7.30	0.08
Average	**1.92**	**10.79**	**0.95**	**-15.08**	**0.41**
Standard deviation	**1.60**	**7.46**	**0.88**	**6.05**	**0.29**

Summary and Conclusions

The research demonstrates how DEA and OLS regression can be combined to estimate gains to DMUs attributed to technical efficiency gains. During the first stage, DEA is used to group DMUs into two groups, namely technically efficient and technically inefficient farmers. The classification is carried forward in the form of a dummy variable to the next stage where production functions are estimated. These production functions are then used to determine benefits to DMUs attributed to technical efficiency gains.

The results indicate that two distinct production functions exist for DEA-determined technically efficient and inefficient farmers. Results further indicate that yield gains are large if farmers are able to produce in a technically efficient manner while maintaining current input levels (movement from DEA-determined technically inefficient to DEA-determined technically efficient production function). However, care should be taken when calculating yield gains, as there are differences between the two production functions. Recall that the estimated production function of the DEA-efficient farmers has a lower curvature than that of the inefficient farmers. In essence these two production functions diverge from each other, which may have resulted in unrealistic yield gains. The procedure thus needs to be validated further with a larger dataset, which would improve the validity of the production functions.

Using the production function of the DEA-inefficient farmers to make input recommendations is a novel approach and should be explored further. Results indicate that even though a producer is technically inefficient, yield gains and therefore increased profits are possible if the farmer adjusts nitrogen application in accordance to tractor utilisation rate (movement on the DEA-determined technically inefficient production function).

It can be concluded that failure to recognise the fact that DEA-determined technically efficient and inefficient producers' production processes are characterised by two distinct production functions renders uniform input recommendations inappropriate. In future, extension officers should aim to develop input recommendations taking these inefficiencies into account.

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