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Title of paper: Technical Efficiency Analysis of Pineapple Production in the Eastern Region of Ghana: Data Envelopment Analysis (DEA) Approach

Author: Henry de Graft Acquah and Emmanuel Kumashie

Abstract

The study examines the technical efficiency level of pineapple farmers and the factors that influence technical efficiency in the Eastern Region of Ghana. Two hundred and seventy one pineapple farmers were selected through a two stage sampling technique. A structured interview schedule was used to gather data relating to farm and farmer specific variables, inputs and output levels. The Data Envelopment Analysis was used to estimate the technical efficiency score. Findings from the study showed that pineapple farmers in the Region were not producing at the optimal level and that 85.85% of pineapple output was not realized as a result of inefficiencies in production. Also, sex, experience, access to credit, use of plastic mulch, and GlobalGAP certification were the factors that influenced technical efficiency in pineapple production.

Key-words: Pineapple, data envelopment analysis, technical efficiency

Author(s) details: Institute of Development Studies, University of Cape Coast Cape Coast, Ghana

Introduction

In Ghana, pineapple is known to be an important horticultural crop and it is mostly grown in the Greater Accra, Eastern, Central and Volta regions. Pineapple is mainly produced for sale in the local market and the export market. In Africa, Ghana is the second largest leading supplier of organic pineapple in the European market after Cote d'Ivoire (Natural Resource Institute, 2010). Statistics from Ministry of Food and Agriculture (MoFA) shows that the total volume of pineapple that was exported in 2009 was 31,566,665Kgs with an equivalent value of US$10,628,200(MoFA, 2012). As Ghana strife's to increase her foreign exchange earnings through export, it is imperative that the country does not only concentrate on cash crops like cocoa and coffee but to also target a horticultural crop like pineapple. The demand for organic pineapple continues to increase in international markets, thus, providing developing countries like Ghana the opportunity to expand their market share. Also, the demand for pineapple by local processing companies is also on the rise.

Although, pineapple export and processing companies have increased over the past few years, the output of pineapple continues to be low. The reasons for low yields has been attributed to lack of technology, unavailability of credit, poor extension services, bad weather conditions as well as improper spacing.For farmers to meet the increasing demand for pineapple then a careful look at their efficiency in production is important. This raises the question: Are pineapple farmers producing at the optimum level? If not, what determines their level of inefficiency?

The objective of this study is to (a) estimate the technical efficiency level of pineapple farmers using the Data Envelopment Analysis and (b) determine the factors that influence technical efficiency by employing the Tobit regression model.

Methodology

Study area

The study was conducted in the Akwapim South Municipality in the Eastern Region of Ghana. The Municipality is bounded on the south by the Ga East and Ga West Districts, on the north by the Suhum Kraboa-Coaltar and Akwapim North Districts and on the west by the West Akim Municipal.

Data and sampling procedure

Primary data was used for the study. The two-stage sampling technique was employed to select 271 farmers who were into pineapple production and a well-structured interview schedule was used to gather information relating to their production activities.

Data analysis

The analytical techniques employed in this study were descriptive statistics and Data Envelopment Analysis (DEA). Data was analyzed using the R Statistical Programming Language as well as the Statistical Package for Social Sciences (SPSS).

Measurement of technical efficiency

The measurement of efficiency has to do with the comparison of actual output to optimal output located on a relevant frontier. It requires an empirical approximation as the true frontier is not known. Approximation of the “best practice” frontier can be done using parametric or non-parametric methods. This paper focuses on the use of DEA which is an example of a non-parametric technique to estimate the technical efficiency level of pineapple producers.

Data Envelopment Analysis is a linear programming method that constructs a non-parametric piece-wise surface or frontier over a data and then efficiency measures are calculated relative to that surface. The efficiency scores obtained from DEA serves as performance indicators to ascertain if farmers operate efficiently. This model as proposed by Charnes, Cooper and Rhodes (1978) is now widely used in empirical studies due to following: this approach is not susceptible to misspecification of errors as it does not impose a functional form on the production frontier and does not make any assumptions about the error term. Also, it does not suffer from multicollinearity and heteroscedasticity and can easily accommodate multiple inputs and outputs. Further, it has been proven that hypothesis testing can be carried out on the DEA efficiency scores after the DEA statistical properties have been defined. This makes it possible to test for DEA model specification, whether there is a significant difference in efficiency scores calculated from two samples and the type of returns to scale exhibited by the technology. However, its application is limited as most of its properties are asymptotic (Banker, 1996). The major flaw of this method is that it is very sensitive to measurement errors as it does not take into account random errors and statistical noise.

The model is specified as follows:

$$\max f_c = \frac{\sum_{r=1}^{s} u_r y_{rc}}{\sum_{i=1}^{m} v_i x_{ic}}$$

$$\text{subject to} \quad \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \leq 1 \qquad (1)$$

$$u_r, v_i \geq 0$$

r =1,…,s; i = 1,…m and j =1,…,n

Where

c = a specific farm firm to be evaluated; y_{rj} = the amount of output r from farm firm j; x_{ij} = the amount of input I to farm firm j; u_r = weight chosen for output r; v_i = weight chosen for input I; n = number of farm firms; s = the number of outputs; m = the number of inputs. The goal of f_c is to maximise the ratio of weight outputs to the weighted inputs of the farm firm under observation and it also defines the objective function. The use of same weights ensures that f_c which is subject to a constraint does not allow any other farm firm in the sample to exceed unit efficiency. Also, these weights are assumed to be unknown but can only be obtained through optimisation. In computing the weights and efficiency measure of f_c, optimisation is carried out separately for each unit.

The problem setting (1) is a fractional program. This can be transformed into linear program (LP) form by restricting the denominator of the objective function f_c to unity and adding this as a constraint to the problem. The LP form of the fractional setting is specified as:

$$\max f_c = \sum_{r=1}^{s} u_r y_{rc}$$

$$\text{subject to} \quad \sum_{i=1}^{m} v_i x_{ic} = 1$$

$$\sum_{r=1}^{s} u_{rc} y_{rj} - \sum_{i=1}^{m} v_{ic} x_{ij} \le 0 \qquad (2)$$

$$u_r, v_i \ge 0$$

r = 1,…,s; i = 1,…,m and j = 1,…,n

The maximising LP setting in (2) assumes constant returns to scale technologies. An input-based efficiency measurement is achieved by formulating the constraints of the weighted sum of the inputs to unity as in (2), and then maximising the outputs. This implies that farm firms minimises the use of in inputs given outputs.

A possible solution to the LP in (2) is to formulate a dual companion. By representing the input weight of firm c by θ_c and the input and output weights of other farm firms in the sample by λ_j the dual form of the maximising problem is formalised as follows:

$$\min f_c = \theta_c$$

$$\text{subject to} \quad \sum_{j=1}^{n} \lambda_j y_{rj} - S_i^{+} = y_{rc} \qquad (3)$$

$$\sum_{j=1}^{n} \lambda_j x_{ij} + S_i^{-} = \theta_c x_{ic}$$

$$\lambda_j, S_i^{+}, S_i^{-} \ge 0$$

$$j = 1, \ldots, n.$$

If the value of θ_c is equal to one then farm firm c is considered to be efficient and the slacks (S_i^{-} and S_i^{+} are zero. That is, if and only if,

$f_c^{*} = 1 \text{with} \, S_i^{-*} = S_i^{+*}$, for all c and j,

where the asterisk represents optimal values of the variables in the dual. It is imperative to draw attention to the fact that the conditions stated also depict the conditions for Pareto efficiency. Thus, it is not possible to improve the observed values of input or output without worsening other input or output values when the farm firm is fully efficient. If the value of θ_c is less than one and/or positive slack variables, then the farm firm is said to be not efficient. For these inefficient farm firms, the optimal values of λ_j construct a hypothetical farm firm, which is formed by the subset of the efficient farm firms.

Observe that the addition of $\sum_{j=1}^{n}\lambda_j = 1$ as an extra constraint to the model (3) considers the variable returns to scale (VRS) in the production (Banker, Charnes & Cooper, 1984).

Determinants of technical efficiency

The second stage after the measurement of technical efficiency is to identify the socio economic variables that influence technical efficiency. The technical efficiency level of farmers is not only determined by farm input combination but it is also influenced by farmer specific characteristics such as age, experience and educational level. Thus, at the second stage, the DEA efficiency scores obtained are regressed on the explanatory variables using either the Ordinary Least Square (OLS) regression or the Tobit regression model. The OLS regression could predict scores greater than one so it has been recommended that the Tobit regression method should be used so as to account for truncated data (Coelli, Rao, O'Donnell & Battese, 2005).The dependent variable, technical efficiency, is a censored variable with an upper limit of one. Thus, DEA score takes a value between 0 and 1, $\left(0 < f^* \leq 1\right)$, as defined in equations (1) to (3). Therefore, the Tobit regression model is adopted for this study.

The standard Tobit model is specified as follows for observation (farm firm) i:

$$y_i^* = \beta' x_i + \varepsilon_i$$

$$y_i = y_i^* \text{ if } y_i^* \succ 0, \text{ and} \qquad (4)$$

$$y_i = 0, \text{otherwise,}$$

where $\varepsilon_i \sim N\left(0, \sigma^2\right)^3$, x_i and β are vectors of explanatory variables and unknown parameters, respectively. The y_i^* is a latent variable and y_i is the DEA score.

The likelihood function (L) is maximised to solve β and σ based on 271 observations (farm firm) of y_i and x_i is

$$L = \prod_{y_i=0}(1-F_i)\prod_{y_i \succ 0}\frac{1}{\left(2\prod\sigma^2\right)^{1/2}} \times e^{-\left[1/\left(2\sigma^2\right)\right]\left(y_i-\beta x_i\right)^2} \qquad (5)$$

where

$$F_i = \int_{-\infty}^{\beta x_i/\sigma} \frac{1}{(2\Pi)^{1/2}} e^{-t^2/2} dt$$

The first product is over the observations for which the farm firms are 100% efficient (y = 0) and the second product is over the observations for which farm firms are inefficient (y > 0). F_i is the distribution function of the standard normal evaluated at $\beta' x_i/\sigma$.

From Table 1, it is evident that on average 32159.04 pineapple output was obtained by using 0.68 hectares of land, 282 person day of labour, 30.31 Ghana cedis of equipment, 678.29 kilogram of fertiliser, 35575.65 number of suckers and 14.89 litres of pesticide. Averagely, the age, household size and farming experience of pineapple farmers in the Municipal are approximately 44 years, 5 and 10 years respectively. The mean age of 44 shows that pineapple production in the Municipal is undertaken by the older generation and Andoh (2007) attributes this to the fact that the youth do not find agriculture lucrative as an occupation.

Table 1: Summary statistics of input output and socio economic variables

Variable	Mean	Minimum	Maximum
Output (Kg)	32159.04	3400.00	200,000.00
Land (Ha)	0.68	0.12	4.00
Labour (P-D)	282.74	3.13	2490.00
Equipment (GHS)	30.31	2.45	171.00
Fertiliser (Kg)	678.29	0.00	171.00
Sucker (No.)	35575.65	1000.00	240000.00
Pesticide (Lit.)	14.89	3.00	56.00
Household size (No.)	5.11	1.00	6.00
Age (Years)	44.17	26.00	70.00
Experience (Years)	10.57	2.00	30.00

Table 2 shows the Tobit regression analysis of the factors that influence technical efficiency. A positive coefficient implies an increase in technical efficiency whilst a negative coefficient shows a reduction in technical efficiency. As expected, gender influenced technical efficiency positively at a significance level of 1%. This results suggests that male farmers are more technically efficient as compared to their female counterparts. This could be due to the fact that men especially those in the developing countries have easy access to wealth and power, therefore they are able to acquire agricultural inputs such as land, labour and capital easily.

Surprisingly, experience in farming has a significant negative relationship with technical efficiency, implying that farmers become technically inefficient when the years spent in farming increases. It is of the view that farmers accumulate knowledge on good farming practices as well as better use of resources as they spend more years in farming, however, the findings in this paper is contrary. This could be explained by the fact that sometimes farmers with long years of farming experience are unwilling to embrace new technologies and good farming practices because they feel more comfortable with their old ways of doing things. Similar result was obtained by Nyagaka, Obare, Omiti and Ngoyo (2010).

As expected access to credit had a positive significant relationship with technical efficiency, indicating that farmers who have access to credit both in cash and in kind are more technically efficient than those who do not have access to credit. Availability and access to credit enable farmers to acquire agricultural inputs such as equipment, improved suckers, fertiliser and pesticides in time for production. It also allows certain management decisions such as land preparation and fertiliser application to implemented in time. This result is in line with that of Obwona (2006).

The coefficient for plastic mulch use and GlobalGAP certification are both positive at a significance level of 5%. This implies that pineapple farmers who adopt the use of plastic mulch and those who have obtained GlobalGAP certification by observing good agricultural practice systems are technically more efficient in production than those who do not. The use of plastic mulch enhances soil moisture retention. Therefore, increasing the use of plastic mulch in production can enhance the technical efficiency of pineapple farmers.

It can also be observed that household size and occupational status are positively related to technical efficiency but they do not have a significant effect on it. The positive sign indicates that farmers with large household size are more technically efficient and those who engage in pineapple production as a full time business are also technically efficient than those who engage in it as a part time business. Families with large household size benefit from it especially during the peak periods when more hands are needed. They are able to carry out certain agricultural activities on time. This finding is consistent with that of Nargis and Lee (2013).

Table 2: Factors influencing technical efficiency: Tobit model

	Coefficients	Std. Error	Z value	Pr((>|z|)
Intercept	-144.77320	35.42645	-4.087	4.38e-05***
Age	0.39841	0.55445	0.719	0.472401
Gender	47.31743	14.92831	3.170	0.001526 **
Hhsize	2.97638	2.17072	1.371	0.170329
EduLevel	-5.21298	4.32654	-1.205	0.228248
Exp	-1.76435	0.90918	-1.941	0.052306 .
Majoccup	25.62514	19.66306	1.303	0.192502
AccCredit	35.83729	9.95605	3.600	0.000319 ***
PlasMulch	24.21429	10.46799	2.313	0.020713 *
GlobalGAP	43.23487	17.04473	2.537	0.011195 *
Log (Scale)	3.95020	0.08768	45.051	< 2e-16 ***

Significance: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Table 3 illustrates the frequency distribution of the technical efficiency level of pineapple farmers. The efficiency score of 1 shows that the farmer is fully technically efficient and a score less than 1 means inefficiency in production. Majority of the farmers representing 88.9% produce below an efficiency level of 0.60. Also, 2.6% of the farmers produce between an efficiency level of 0.71 and 0.80 whilst 3.3% produce between an efficiency level of 0.91 and 1.00.The least and highest technical efficiency levels are 0% and 100% respectively whilst the average technical efficiency level is 14.15%. This means that there is a high level of inefficiencies in pineapple production in the Municipal and this has led to a reduction in output by 85.85%. The technical efficiency level in this study is low as compared to other studies by Ayaz, Hussain and Sial (2010) and Nargis and Lee (2013).

Table 3: Frequency distribution of technical efficiency

Technical efficiency	Farmers	Percentage (%)
<0.60	241	88.90
0.61-0.70	9	3.30
0.71-0.80	7	2.60
0.81-0.90	5	1.80
0.91-1.00	9	3.30
Mean		14.15
Minimum		0.00
Maximum		100.00
Total farmers	271	

Conclusion

The Tobit model was used to explain the farmer specific characteristics that influence technical efficiency in pineapple production. Results revealed that farmers who are into pineapple production are not technically efficient and that output could be increased by 85.85% without employing additional inputs. Also, analysis from the Tobit regression showed that sex, experience, access to credit, use of plastic mulch and GlobalGAP certification had a significant influence on technical efficiency. The Ministry of Food and Agriculture through agricultural extension agents should educate and train farmers on the use of plastic mulch and the adoption of good agricultural practices.

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