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An Application of Data Development Analysis to Evaluate The Technical Efficiency of Pineapple Farms in Johor, Malaysia

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Abstract

Pineapple farming has become a crucial part of Malaysia's agriculture. This study aims to evaluate the performance of pineapple farms in Johor by analysing their technical efficiency and identifying the factors that influence their technical efficiency. To determine the technical efficiency levels of pineapple farms, the Data Envelopment Analysis (DEA) method was applied, and Tobit analysis was used to examine the technical efficiency drivers. A field survey was undertaken from June to December 2021 to choose a sample of 290 pineapple farmers for this study. The data were collected from a single pineapple cropping season from 2019 to 2020. The results indicate that the average technical efficiency under constant returns to scale (CRS) and variable returns to scale (VRS) were 0.96. Furthermore, education level, annual contact and engagement with extension agents, membership in farmer's associations, being a full-time pineapple farmer, and participation in farming courses and study visits all have a favourable and significant effect on farm management efficiency. The primary issue with pineapple cultivation in Johor is inefficient agricultural techniques, in which growers do not maximise the use of available agricultural inputs. According to the findings, farmers' knowledge and abilities in pineapple growing must be improved through agronomic education.

Keywords: Pineapple, Production Function, Data Envelopment Analysis, Technical Efficiency

Introduction

The pineapple sector is essential to Malaysia's agri-food sector. With over a century of expertise in the pineapple sector, Malaysia has a competitive edge in the international market. While agricultural development strategies in Malaysia aim to improve productivity, competitiveness, and sustainability in the agro-food industry and the income of producers, the competitiveness of the pineapple sector, is seen as critical to the country's economic progress (Jaji *et al*., 2018). Through the Malaysian Pineapple Industry Board (MPIB) and the Ministry of Agriculture and Food Industries (MAFI), the government has designed various initiatives and frameworks to enhance the efficiency of the pineapple industry throughout the value chain to make agricultural development more productive and competitive (Malaysian Pineapple Industry Board, 2016).

The Malaysian pineapple industry is managed and coordinated by the Malaysian Pineapple Industry Board (MPIB), an agency under MAFI established in 1957 under the *Ordinan Perusahaan Nanas* 1957. In 1990, *Ordinan Perusahaan Nanas* 1957 was repealed and replaced with *Akta Perindustrian Nanas Malaysia* 1957 (*Semakan,* 1990). In Malaya, pineapples were planted between the fledgling rubber trees and in fields of their own. Pineapple cultivation evolved well in Johor Barat starting in 1921 in place of the rubber industry development. The rubber industry was having poor growth in 1931 and affected pineapple cultivation. This created awareness that pineapple is an important crop to be planted as single planting considering its' contribution to Malaya's economy.

Pineapple's role in Malaysia's economy extends beyond its role as a source of food, as its cultivation also provides farmers with a crucial source of revenue and new employment opportunities (Rozhan, 2017). Pineapple is produced throughout all states in Malaysia. In 2020, pineapples occupied approximately 15,849.77 hectares of land. About 75.5% of the pineapple farmland (11,968.80 ha) is located in Peninsular Malaysia, while Sabah and Sarawak constitute 6.4% (1,021.90 ha) and 18.0% (2,859.07 ha) respectively in 2018 (Malaysian Industry Pineapple Board, 2021).

The distribution of pineapple land areas among eleven states in Malaysia shows that Johor has the highest allocation (8,554.14 hectares), which constitutes 54% of the total pineapple areas (15,849.77 hectares) in the country in 2020. The pineapple land allocated to other pineapple states and their proportions of the total areas are Sarawak (18%), Sabah (6.5%), Kedah (5.4%), Pahang (4.3%), Selangor (4%), Perak (2%), Kelantan (1.8%), Terengganu (1.3%), Negeri Sembilan (0.72%), Melaka (0.3%) and Perlis (0.04%) (Malaysian Industry Pineapple Board, 2021). From 1997 to 2018, as shown in Figure 1, the country's crop area and production have been in upheaval. However, as previously stated and discussed, there is some variation, such as in 2000, 2006, and 2016, when production increased. In recent years, pineapple production has increased, which has resulted in larger pineapple yields. As a result of the Malaysian government's intervention through MPIB, pineapple yields have increased as compared to the trend's planted areas.

The pineapple's production from 2000 till 2020 has shown a fluctuating trend. This was due to a few factors. This includes the factor of the emphasis given by the government through different policies set by government mandate through Malaysia Plans. Eighth Malaysia Plan (RMKe-8) (2001-2005), Ninth Malaysia Plan (RMKe-9) (2006-2010), Eleventh Malaysia Plan (RMKe-11) (2011 – 2015), and Twelfth Malaysia Plan (RMKe-12) (2016 – 2020), each of these plans has a different highlight of crops (Economic Planning Unit, 1980, 1986, 1991, 2000, 2001, 2015). However, the yield of pineapple has been continuously substantially decreasing from 2016 until 2020 as shown in Figure 1.2. Profitability for pineapple growers is proportional to yield, with a higher production resulting in a greater revenue. Nevertheless, market pressures such as pineapple prices and input costs persist, impacting pineapple production in Johor, where pineapple prices and input costs are uncertain as a result of the current economic climate (demand, supply, world market prices).

Pineapple plantations necessitate efficient resource management and all agricultural operations in order to achieve a high yield at a low cost while also increasing farm profit. Farm production and productivity are governed by farm management efficiency, which is tied to the efficient exploitation of resources, including agricultural inputs, capital, labour, and land. Particular preferences for resources contribute to the diversity of farm performance, where the combinations of input utilisation have varying effects on the output maximisation of individual farms. In addition, pineapple cultivation practices vary among farmers based on their geographical and socioeconomic backgrounds. In addition, the involvement of extension agents in pineapple cultivation may influence the agricultural tactics of farmers. Agents of extension provided farmers with information on pineapple-growing technologies. In pursuit of further supporting the maximum development of the pineapple industry in Malaysia (Jaji *et al*., 2018), this study's objective is to assess the productivity of smallholder pineapple farmers in Johor by analysing the level of technical efficiency among farms and determining the causes of technical efficiency on smallholder pineapple farms. It will identify places where adjustments can be made to aid pineapple producers in raising output levels. The outcomes of this research may be relevant for policymaking.

Efficiency Concepts

Michael Farrel established efficiency studies in 1957, expanding on Debreu (1951); Koopmans's (1951) work. Farrel (1957) established two efficiency measurement concepts: input-oriented and output-oriented. The input-oriented measures aim to reduce input quantities while maintaining output quantities. The output-oriented concept determines how much output should expand without modifying the inputs. This study, however, utilised output-oriented measurements with an emphasis on output maximisation. Technical efficiency (TE) is attained when a farmer is able to maximise production with a given set of inputs by utilising existing technology.

Previous Studies

There are a number of publications concerning the effectiveness of pineapple production in Malaysia. Rahim and Othman (2019) examined the resource use efficiency in pineapple growing in Johor. In 2017, 88 respondents were selected for her study. They discovered that farms were not making use of economies of scale because the majority of pineapple producers have small-sized farms, which would result in higher production costs and lower profits. This indicates that small farms were not exploited as efficiently as large farms, which negatively impacted farm productivity.

The technical efficiency of pineapple smallholders in Johor was low and further evidenced that it came from improper use of variables. The findings also found that the farmers are operating under decreasing returns to scale. This indicates that farmers should minimise the cost of production in order to boost yield. Meanwhile, Idris *et al* (2013) studied pineapple's technical efficiency in Kota Samarahan, Sarawak, and from the survey, the farms were also generally technical inefficient. The study found that family labour, years of farming experience and participation in agricultural associations are important and significant determinants of technical efficiency for the agricultural project.

Methodology

Data

The field survey was conducted between June and December of the year 2021. The survey covered the Data covered the seven districts in Johor, including Muar, Batu Pahat, Pontian, Kluang, Kota Tinggi, Johor Bahru and Segamat, due to their relative importance in pineapple production. Pineapple farmers were selected by each district using a stratified proportionate random sampling method. The number of respondents was set according to the total number of pineapple farmers registered by MPIB. Using a standardised questionnaire, face-to-face interviews were conducted to collect data. Face-to-face interviews are the most effective mode of data collecting because interviewers may clarify questions, dispel misunderstandings, and encourage respondents if they do not comprehend the questions and questionnaire structure. Moreover, face-to-face interviews are highly beneficial for illiterate potential respondents. Three hundred twenty-nine questionnaires were collected; however, some information, particularly production factor components, was incomplete. Only 290 surveys were valid for analysis following the data cleaning procedure. The number of samples represented 32.3 per cent of the population. Following Cochran *et al* (1977), a population of 899 might be represented by a minimum of 270 sample respondents. As a result, the number of samples effectively represented the population of pineapple producers in Johor.

Data Envelopment Analysis (DEA)

Data Envelopment Analysis (DEA) is a non-parametric estimation technique that employs mathematical programming. The farmer is the Decision-Making Unit (DMU) responsible for regulating input and output. To quantify efficiency, the DEA method calculates the ratio of weighted output to weighted input. The ratio varies between 0 and 1. In DEA, it is expected that deviation factors result from inefficiency, however, if noise is present, it affects the location of the DEA frontier (Coelli *et al*., 1998). The efficiency ratings are calculated, as opposed to being approximated. This is why the DEA model is not considered a statistical method. Constant returns to scale (DEA-CRS) and variable returns to scale (DEA-VRS) are the two primary DEA models (DEA-VRS). In 1978, Charnes, Cooper, and Rhodes proposed the DEA-CRS model, which is also known as the CCR model. The CRS model is described as follows by Charnes *et al*. (1978):

$$Min_{\theta,\lambda} : \theta$$

$$\text{Subjected to} \quad \begin{aligned} -\theta y_i + Y\lambda &\geq 0, \\ \theta x_i - X\lambda &\geq 0, \quad (1) \\ \lambda &\geq 0 \end{aligned}$$

Where θ is i-th farm's score of technical efficiency (TE), y_i is the yield of pineapple of i-th farm and the quantity of inputs used by that farm are x_i. It is reasonable to assume N is the number of farm, with each farm having its own set of variables (X) where Y represents output for N farms, X represents input for N farm, λ is a vector of constants Nx1, and θ is a scalar. Efficiency estimation on the frontier is done using $Y\lambda$ and $X\lambda$.

The value θ represents efficiency score of farm which is constrained by the value of 0 and 1 in the range. There is full technical efficiency if θ value is equal to 1 (θ=1), and there is technical inefficiency if the value is less than 1 (θ<1). The value obtained (θ-1) indicates the proportional increase in output that might be obtained by the i-th farm decision making unit (DMU) with constant input quantities.

In the DEA-CRS restriction, it is assumed that all DMUs are operating at optimal scale; hence, scale efficiency (SE) confounds the measurement of technical efficiency (TE). The extension of the DEA-CRS model developed by Banker, Charnes, and Cooper is the DEA-VRS model. This model is also referred to as the BCC model (Banker *et al*., 1984). The convexity constraint $N1'\lambda$, is added to the DEA-CRS model to produce the DEA-VRS model as follows:

$$Min_{\theta,\lambda}\theta,$$

$$\text{Subjected to} \quad \begin{array}{l} -y_i + Y\lambda \geq 0, \\ \theta x_i - X\lambda \geq 0, \\ N1'\lambda = 1 \\ \lambda \geq 0 \end{array} \quad (2)$$

$N1'$ is a vector of $(N \times 1)$ and a convexity restriction whereas λ is $(N \times 1)$ a vector of intensity variables. 1≤θ<∞ and θ-1 is the output quantities that increase when input quantities remain constant. The adoption of the DEA-VRS model permits the separation of technical efficiency from SE effects. SE is the ratio between the average output of a farm operating at the point and the average output of a farm operating at the point with technical efficiency.

Tobit Analysis
Tobit analysis was employed to determine the socioeconomic and farm-specific elements that affected the technical efficiency of farm management. Tobin (1958) is credited with developing the Tobit model. Y, the response variable in the Tobit model, ranges between 0 and 1. This model is also known as the censored normal regression model because it only observed values of Y larger than zero. If the value of Y is zero or less than zero, however, Y is neither observed nor censored.

$$y^*i = x_i\beta + u_i$$
$$y_i = y^*i \quad if \quad y^*i > 0$$
$$y_i = 0 \quad\quad if \quad y^*i \leq 0$$

Where y* represents the latent dependent variable, x_i represents the explanatory variable, y represents the observed dependent variable, β indicates the coefficient to be estimated, and u_i is independently normal distributed $N\left(0,\sigma^2\right)$. Socioeconomic and farm-specific inefficiency factors were individually regressed with DEA scores to determine the efficiency and inefficiency causes.

Findings and Discussion

Explanation of Variables
Table 1 displays the summary data for the variable utilised in the assessment of efficiency. The average pineapple yield was 18.6 ton/ac and the average for suckers, fertiliser, labour, agrochemicals and hormones were 14,739 suckers/ac, 1,522.2 kg/ac, 55.8 man-days/ac, 11.1 l/ac, and 5.25 l/ac. Fertiliser is the most expensive input due to its high cost relative to other

inputs. The farms used a minimum of 35 and a maximum of 75 man-days of labour. Labour is measured by man-days per cropping season.

a. Summary statistics of determinants of efficiency

Under the non-parametric approach, the farmers' socioeconomic and institutional factors were modelled and estimated using the Tobit model as determinants of inefficiency to understand how these factors influence the level of inefficiency of the pineapple farmers in the study area. As determinants of efficiency, eight explanatory variables were utilised, including farmers' age, level of education, household size, farming experience, non-farming activities, contacts with extension agents per cropping cycle, membership in a farmers' organisation, and participation in courses and study visits. The education level is divided into five categories which are no formal education, primary school only, secondary school, bachelor's degree, and postgraduate studies.

The average level of education is 3.2, indicating that the majority of farmers attended secondary school. Minimum farming experience is one year, and the highest experience is 40 years, with an average of 7.8 years. The minimum age of farmers in the sample is 18 years old, the maximum age is 85 years old, and the average age is 50 years old. The minimal number of contacts with extension agents every cropping cycle is zero, while the maximum number of contacts is ten. The majority of the 185 farmers who make up the farmer's association are members. In addition, 165 of 290 farmers specialise in pineapple farming compared to others who had off pineapple farming which is farming other crops and has other occupations. This implies that 125 pineapple farmers engage in activities other than pineapple cultivation. Only 265 farmers have participated in agricultural courses, seminars, and study visits to pineapple farms.

DEA Results

Data Envelopment Analysis, a computer programme, was used to estimate the data (Coelli *et al*., 1998).Table 2 lists the farm's technical efficiency scores. The mean of technical efficiency under both the TEcrs and TEvrs assumptions is 0.96. At the same input level, farmers only produce 96% of the output of best-practices farms (CRS and VRS). In order to maintain the same level of production, farms must increase their efficiency in the use of inputs by around 4% (VRS).

Efficiencies for pineapple farms under TEcrs varied from 0.905 to 1 and ranged from 0.913 to 1 under TEvrs. Twenty-two farms are technically efficient under TEcrs, while 39 farms were technically efficient under TEvrs. This indicates that there are more farms reaching complete technical efficiency under the TEcrs assumption than under the TEvrs assumption. Technical efficiency was greater under the DEA-CRS model than the DEA-VRS model, indicating that the DEA-CRS model is more flexible and encloses the data more tightly. Scale efficiency (SE) scores of farms ranged from 0.953 to 1.000, with 91 farms being scale efficient and a mean value of 0.994. Mean farm scale efficiency was relatively high, indicating that agricultural inefficiencies are related to inefficient utilisation of inputs.

Table 3 illustrates the returns to scale for the sample farm. There were three categories for farms: sub-optimal (IRS), ideal (CRS), and super-optimal (DRS). Approximately 16.55 per cent (48 farms), 31.37 per cent (91 farms), and 52.07 per cent (151 farms) of farms, respectively, were sub-optimal, optimal and super-optimal. Therefore, the majority of farms exhibit decreasing returns to scale. Sub-optimal farms should increase the efficiency of input usage to boost yield, while super-optimal farms should decrease input use to increase profits.

Determinants of Technical Inefficiency

Table 4 presents the technological inefficiency's determinants. Age, education, farming experience, extension visits, participation in a farming association, and seminar attendance have all been shown to have negative effects on technical inefficiency, indicating that they lower technical inefficiency.

Age has a negative correlation with productivity among farmers. Young farmers are less efficient than older farmers. However, the age of farmers has no significant effect on inefficiency. Insignificantly, an education degree has a detrimental impact on technical inefficiency. Farmers with education are more productive than farmers without schooling because it is simpler for farmers with education to absorb farming information, knowledge, and skills through extension agents' reading materials.

Farming experience has a negative relationship with farmers' inefficiency. In the case of Johor, the pineapple farming experience was negative and significantly influenced technical inefficiency at a ten per cent level of significance. These findings disagree with research conducted among pineapple smallholders in Osun State in Nigeria by Adegbite *et al*. (2014) and Sarawak state in Malaysia by (Idris *et al*., 2013). The higher and more experienced farmers are less inefficient, and this was proven by the concentration of government funding and assistance to farmers in Johor historically over the decades. The number of contacts with extension agents per year has no significant effect on technical efficiency but negatively correlates with technical inefficiency.This means that higher extension visits would increase the efficiency of pineapple farms. Further variables that contradict Idris *et al* (2013) and Lubis *et al*. (2014) were participation in the farming association. Joining farmers' associations negatively influences inefficiency, but it is not significant. The benefits of joining a farmers' association include consultation services, obtaining subsidies and marketing facilities.

Meanwhile, attending farming courses and study visits has a significant relationship with technical efficiency. Attending farming courses and study visits has a significant relationship with technical efficiency at 5 per cent. Farmers who attend higher educational farming seminars, courses and programmes are more efficient than farmers who have lesser attendance.

The advantages of joining a farmers' organisation include consultation services, the ability to get subsidies, and a marketing facility. In the meantime, participation in agricultural courses and study trips has a significant association with technical efficiency. Attending farming courses and study visits has a significant relationship with technical inefficiency at a five per cent level of significance. Farmers who attend farming seminars, courses, and programmes at a higher level of education are more productive than those who attend less frequently.

However, in the case of pineapple farms in Johor, household size and off-farm activities were having positive effects on technical inefficiency. This study concurs with studies conducted by (Lubis *et al*., 2014). Further, off-farm activities were found to have significant effect on technical inefficiency at a ten per cent level of significance. This implies that off-farm activities by the farmer have increased their inefficiency, and the full-time farmers who focus on pineapple cultivation are more efficient. Farmers who cultivate pineapple as their primary income crop are more efficient than those who grow other crops because they devote more attention to their primary revenue crop. Concerning household size, this variable is crucial as for smallholders; family labour contributes to their efficiency. It was found that a larger household size increases inefficiency, but the relationship is not significant. Concurring with Akhilomen *et al* (2015), the coefficient of household size among pineapple farmers in Nigeria positively affected technical inefficiency.

Conclusion

This study analyses the technical efficiency of pineapple farming in Malaysia by selecting Johor as the largest pineapple producing state. The research have employed 290 smallholders farms using cross-sectional data from the 2020/2021 cropping season. Using the data envelopment analysis method, technical efficiency is estimated. Numerous factors, such as age, non-agricultural activities, and extension trips, were studied for their effect on technical efficiency. The pineapple farmers in the present study are technically inefficient. The major problem associated with pineapple farming in Johor is poor agricultural practices where farmers do not fully utilise the available agricultural inputs to produce maximum output. The farming experience was found to be decreasing the technical inefficiency of the farmers. Thus, strategies by farmers should be made for the experienced pineapple farmers to focus on sharing and delivering their good experience in pineapple farming in the study area.

The fact that some factors have shown to have significant contribution to pineapple smallholders technical efficiency (farming experience and off farm activities) implies that pineapple production could be improved upon if efforts are stepped up to appropriately improve the usage of these factors as there is potential for increasing farm efficiency by adopting current farming technologies by the experienced farmers and farmers who have off farm activities. More knowledge transfers by the theme that was employed by the experienced farmers to farmers are therefore recommended. Thus, such knowledge could help improve the efficiency with which these factors are being utilized. Farmers should be frequently educated on current, diverse culturing skills and techniques on pineapple production, thus the knowledge could be disseminated to Malaysian pineapple farmers through reskilling and upskilling programmes such as short-courses, mentoring and application of smart farming practices.

Government and relevant agencies such as the regulating body of the pineapple industry in Malaysia should provide seminar to pineapple farmers to educate them about good agricultural practices. Campaigns to advocate for farmers participating in seminars by the experienced farmers should be encouraged further as it was found that farming experience decreases technical inefficiency. Furthermore, the technical inefficiency of the farmers was significantly reduced when farmers had off-farm activities. Efforts should be made to increase the farmers' awareness, to put an emphasis in their agronomic and time invested in the farm management as this may increase their level of technical efficiency.

The outcomes of this study demonstrate that pineapple farms are technically inefficient, with a low mean level of technical inefficiency. Farms are inefficient in their input use and hence do not produce optimum pineapple production, resulting in cost minimisation and not maximising profit. Improper farm management and misallocation of inputs are to blame for the inefficiencies. Farmers must enhance their farm management skills by attending agronomic education sessions by extension agents.

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Tables, Graphs, Figures

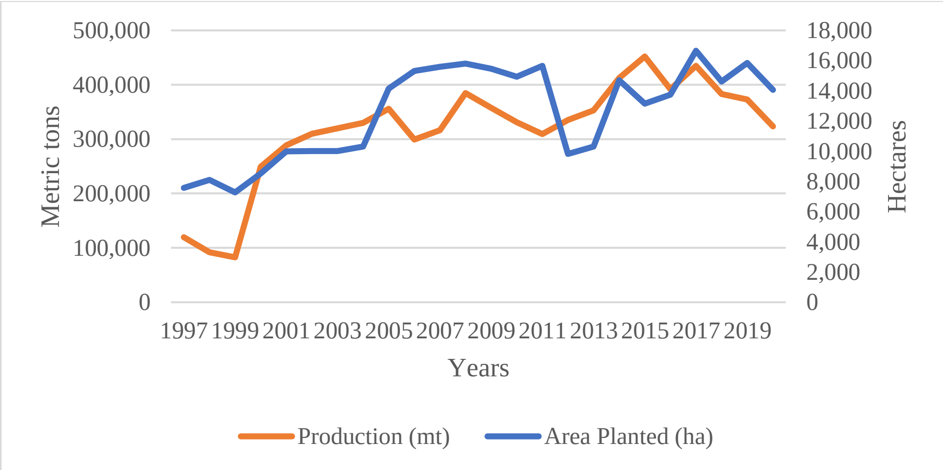

Figure 1: Pineapple production (tons) and area harvested (ha) in Malaysia, 1997 - 2020
Source: (MPIB Yearly Reports, 2010-2021)

Table 1
Summary statistics of variables used in the efficiency analysis

Variable	Total	Mean	Minimum	Maximum	Std. Dev.
<u>Output</u>					
Fresh pineapples	290	18.6	10.8	33.0	3.83
<u>Inputs</u>					
Land (ac)	290	2.3	1	11	1.4
Suckers (no/ac)	290	14,739	10,000	18,500	1,421.4

Fertilizer (kg/ac)	290	754.1	450	1050	109.8
Labour (man-days/ac)	290	55.8	35	75	11.7
Agrochemicals (l/ac)	290	11.1	5	25	4.1
Hormones (l/ac)	290	5.25	2.7	7	0.85
Age	290	50.1	18	85	13.9
Education Level	290	3.2	1	5	0.8
Household Size	290	4.4	1	13	2.2
Farming Experience	290	7.8	1	40	7.1
Off-farm activities	125	0.57	0	1	0.49
Contacts with extension agents	290	4.2	0	10	0.9
Farmer's association membership	185	0.64	0	1	0.48
Seminar attended	265	0.9	0	1	0.28

Table 2
Efficiency scores of farms under DEA

Efficiency Index	TEcrs	TEvrs	SE
0.100 -0.199	0	0	0
0.200 – 0.299	0	0	0
0.300 – 0.399	0	0	0
0.400 – 0.499	0	0	0
0.500 – 0.599	0	0	0
0.600 – 0.699	0	0	0
0.700 – 0.799	0	0	0
0.800 – 0.899	0	0	0
0.900 – 0.999	268	251	199
1.000	22	39	91
Min	0.905	0.913	0.953
Max	1	1	1
Mean	0.96	0.96	0.994
Standard deviation	0.026	0.026	0.007

Table 3
Characteristics of farms with respect to returns to scale

Characteristics	Number of farms
Sub-Optimal (IRS)	48
Optimal (CRS)	91
Super-Optimal (DRS)	151

Table 4
Determinants of technical efficiency

Explanatory Variable	DEA

	Coefficient	Standard Error	Probability Value
Constant	0.256***	0.081	0.001
Age	-0.022	0.017	0.208
Education	-0.014	0.011	0.209
Household Size	0.002	0.007	0.751
Farming Experience	-0.009*	0.005	0.078
Off-Farm activities	0.020*	0.011	0.071
Extension visit	-0.005	0.013	0.640
Membership	-0.004	0.008	0.611
Seminar attended	-0.001	0.007	0.845

Source: Field survey data (2021).

Note: *,** and *** denote significance at 10%, 5% and 1% level respectively.