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DATA ENVELOPMENT ANALYSIS OF RUBBER SMALLHOLDERS: BCC AND CCR MODELS AND BOOTSTRAPPING TECHNIQUE

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Abstract

The present study examined the economic efficiency of rubber smallholders in Peninsular Malaysia in a disaggregated form using Banker Charnes and Cooper (BCC) and Charnes Cooper and Rhodes (CCR) models of data envelopment analysis (DEA) as well as their respective bootstrap techniques. Multistage data collection was employed on 327 smallholders among 5 districts of Negeri Sembilan state. However, only 307 observations were used in computing inferential statistics, because the young-age category has been removed. The districts include Seremban, Tampin, Rembau, Kuala Pilah and Jempol. The results revealed that, the mean technical efficiency (TE) under variable returns to scale (VRS) and constant returns to scale (CRS) were 0.95, 0.97 0.96 and 0.45, 0.61, 0.33 for the all-age, matured-age and old-age crops respectively. The findings of the result also disclosed that naïve DEA has higher mean scores than bootstrapped-DEA, thus indicating the presence of bias in the former and absence of bias in the later. Also, the efficiency determinants under VRS and CRS as well as their respective bias-corrected (BC) efficiency scores were also analyzed using Tobit regression analysis against the 15 socio-demographic factors. It was found out that critical factors, common to all the age-categories, include educational level, tapping system and marital status under VRS and BC-VRS assumptions, while under CRS and BC-CRS assumptions include race, tapping system, marital status and farm's distance. Therefore, education of smallholders should be given more attention to increase efficiency. The study finally recommends that the traditional concept of computing efficiency or productivity of rubber and other perennial crops in an aggregated form should be complemented with the disaggregated form as this eliminates any bias and gives meaningful results. Improved methods such as bootstrapping should also be used as this only gives what is called bias-corrected efficiency scores. Regarding the determinants, factors such as education, tapping system and farm distance should be given more emphasis.

Keywords: Data Envelopment Analysis; Variable Return to Scale; Constant Return to Scale; Rubber Smallholders; Malaysia.

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1. Introduction

Data Envelopment Analysis (DEA), which is a non-parametric method or approach, was one of the earliest approaches to technical efficiency measurement proposed by Farrell, (1957) and later developed by Charnes, Cooper and Rhodes (CCR, 1978). The idea of CCR was specifically on constant return to scale assumptions. However, in 1984 a new and improved version of DEA was developed but this time it was based on variable return to scale assumptions and was proposed by Benker, Cooper and Charnes (BCC, 1984). The technical efficiency scores of BCC are higher in terms of magnitude than their CCR counterpart. DEA measures the relative efficiency score ranging from 0 to 1 as a result of the division or ratio of output to input of every decision making unit (DMU) Avkiran (1999). An efficiency score of 1 is assigned to the "best firms" that is most efficient and positioned on the frontier, while zero (0) is assigned to the least efficient firms. The efficiency level is represented by the distance to the frontiers ,with an assertion that the farthest away from the frontier, the lowest its level of efficiency which in turn implies the lowest its efficiency score (between 0-1) (Latruffe et al 2010).

Apart from the pioneering work of Farrell, (1957), non-parametric research approaches have been cited and re-cited in efficiency literatures. For instance, more than two decades after Farrell's work, a CCR model of DEA has been introduced into the literature by Charnes, Cooper and Rhodes (1978). Shortly after that, another DEA model known as BCC was introduced by Benker, Cooper and Charnes (BCC) (1984). As said earlier, CCR model uses the concept of constant return to scale to analyze production efficiencies of the decision making units (DMU) in a multivariate settings while the BCC model uses the concepts of Variable returns to scale (VRS).

1.1. Overview of Rubber Productivity in Malaysia in Recent Years

Starting with table 1 which is the total productivity or yield of Malaysian rubber, consists of the values of both the estate and the smallholders productivity combined. About 30 year time series data drawn from statistics department of Malaysia displayed 4 columns which include total area planted in hectares, total production in tonnes, and total productivity in tonnes per hectare as well as total productivity in kilogram per hectare for 30 years from 1982 until 2012. A careful observation of the table indicated that Malaysian rubber yield productivity has increased especially during the period between 2004 to 2007, with 2006 as the most lucrative year Malaysia ever experienced in terms of rubber productivity having an estimated quantity of 1,216 kg/ha which is equivalent to 1,.34 million tonnes per hectare.

However, the rubber productivity started declining again shortly after 2007. This decline in productivity trend might be as a result of decrease in production capacity. This is because as can be seen from the table, that the total rubber planted area was increasing from 2009 until 2012, yet productivity was coming down. So regarding this trend, the rubber yield productivity is going in a direct proportion with production but partly in an inverse proportion with planted area. So summing it up, the rubber yield is declining was due to among other things, low production capacities which in turn might be affected due to other influencing factors.

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Table 1: Malaysian total rubber productivity for the period 1982-2012

Years	Area (000 ha)	Production (000 MT)	Productivity (Mt/ha)	Productivity (Kg/ha)
1982	1,991.6	1,494.1	0.75	680.57
1983	1,971.0	1,563.7	0.79	719.72
1984	1,972.7	1,530.6	0.78	703.88
1985	1,955.4	1,469.4	0.75	681.71
1986	1,912.0	1,538.6	0.80	730.02
1987	1,881.3	1,578.7	0.84	761.27
1988	1,865.8	1,661.6	0.89	807.90
1989	1,849.0	1,415.6	0.77	694.55
1990	1,836.7	1,291.0	0.70	637.66
1991	1,818.7	1,255.7	0.69	626.36
1992	1,792.3	1,170.9	0.65	592.66
1993	1,762.8	1,074.3	0.61	552.87
1994	1,737.1	1,100.6	0.63	574.78
1995	1,688.8	1,087.5	0.64	584.18
1996	1,644.3	1,082.3	0.66	597.12
1997	1,616.5	971.1	0.60	544.99
1998	1,543.6	883.5	0.57	519.24
1999	1,464.8	777.8	0.53	481.71
2000	1,430.7	926.2	0.65	587.29
2001	1,389.3	882.0	0.63	575.93
2002	1,065.9	890.0	0.83	757.48
2003	1,021.3	985.7	0.97	875.57
2004	976.6	1,168.6	1.20	1085.54
2005	957.8	1,126.0	1.18	1066.50
2006	957.1	1,283.6	1.34	1216.66
2007	976.2	1,199.6	1.23	1114.80
2008	986.2	1,072.4	1.09	986.48
2009	1,015.1	857.0	0.84	765.90
2010	1,015.2	939.2	0.93	839.28
2011	1,012.8	996.2	0.98	892.32
2012	1,059.7	922.8	0.87	789.99

Source: Malaysian Department of Statistics, (2015)

The values in the fourth column of table 1 which represents the total productivity in kg/ha, are presented in form of a line graph. The statistical trend of almost 30 years of time series data ranging from 1982-2012, was plotted using the figures of the table 1 which in turn sourced from the Malaysian department of statistics. The figure also revealed that rubber productivity have initially increased, then maintained a fairly stable flow, increased to a certain level and thereafter started to decline.

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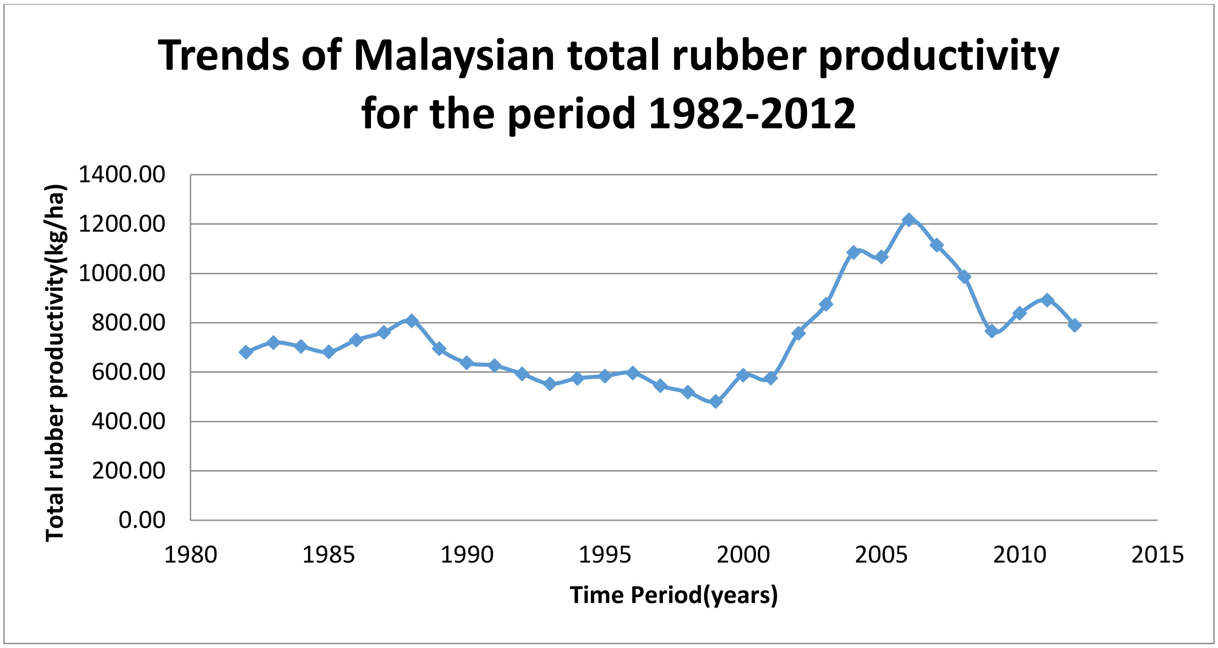

Figure 1: Trends of Malaysian Total rubber productivity for the period 1982-2012
Source: Malaysian Department of Statistics.

1.2. Problem Statement

The research journey has begun by carefully examining the trends of rubber productivity in Peninsular Malaysia through plotting of nearly 30 year period of time series data obtained from statistics department of Malaysia. The duration of the time period ranged from year 1982 to 2012 as shown the table.

Comparing the figures in the table, it would be observed that the values of rubber planted areas, volume of production and productivity yield (kg/ha) of rubber, have initially indicated the declining trends of rubber productivity especially from 2010-2012. Deductions from such movement specifically showed that, all the 3 parameters -planted area, production capacity and productivity (kg/ha) of rubber, have an unpredictable scenario and this led us to holistically investigate if the capacity and capabilities of the smallholders, under Malaysian present economic transformation programs, are operating at a level of economic efficiency adequately enough to justify their future strength and survival in the rubber industry in Peninsular Malaysia. In making thorough investigations, this study sought to examine the perenniality nature of the rubber farms by analyzing rubber in a disaggregated form, since most of the smallholders' previous studies on technical and economic efficiencies of rubber production were carried out on aggregated data and since the results of these estimates are subject to aggregation bias because perennial crops such as rubber vary in yield according to age of crops. In an attempt to fill in this gap, there is a need to compute and find out if there is any bias or difference between the efficiency scores of aggregated and disaggregated rubber crops ages.

However, this study is specifically looking at the following research questions

1) Are the Malaysian rubber smallholders' technical efficiencies sufficient to guarantee their future survivals in the rubber industry?

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2) Considering the perenniality nature of rubber crops, which has varying growing pattern throughout its life span, are there any disparities or bias in the technical efficiency scores between aggregated and disaggregated crops ages?
3) What are the likely factors or determinants influencing rubber smallholders' efficiencies?

1.3. Objectives of the Study

The general objective of the study was to analyze the technical efficiency of Rubber Smallholders in Negeri Sembilan, Malaysia.

The specific objectives included the following viz:

1) To determine the mean technical efficiency scores of rubber smallholders in Negeri Sembilan according to age-categories using both VRS and CRS.
2) To investigate and analyse the presence/absence of aggregation bias in the efficiency scores among the three crops-age categories using the bootstrapping technique of both the VRS and CRS.
3) To identify and estimate determinants militating against technical efficiency scores using Tobit regression analysis.

2. Literature Review

Kiatpathomchai *et al*, (2009) used two stage data envelopment analysis (DEA) to analyze and assess the technically efficient frontier of paddy farms in southern part of Thailand. The investigation was done using input orientation and the results indicated that, although output of 3.5 tons/ha of paddy rice should be maintained, but reduction of inputs to about 8-14% is encouraged and thus, recommended. They also suggested that newly improved rice varieties should be used instead of old traditional species.

A two-stage DEA was also used in estimating technical efficiency of Macedonia pig farms by Marina *et al* (2012). The results revealed that 94% and 47% technically efficient according to VRS and CRS assumptions respectively. The ratio between the two Technical efficiencies gave scale efficiency of 47%. The results of the second stage analysis has indicated that ,adopting or using new technologies positively influenced farm productivity and thus, higher technical efficiency. It further indicated that farmers with high educational levels are more early adopters and more flexible in the application of the new technologies, and this suggest that farmers should increase their capacities for both formal and informal education.

Latruf *et al* (2010) conducted an investigation on technical efficiency and pressures exerted by environment on Hungarian pig farms. The study specifically looked at how and to what extend has the environmental regulations, if enforced on Hungarian pigs, would affect the farm's technical efficiency. The analysis was done on two separately pig farming systems known as Farrow to finish and finishing farms respectively as FAFI and FI farms. The result has showed that the farmers have both the capacity and capability to cut down the nitrogen pollution to increase the efficiency even if environmental regulations has not been tempered with or enforced.

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Ogunniyi and Ajao (2011) used both the parametric and Non-parametric approaches to measure technical efficiency of maize farm production in Oyo state, Nigeria. Maize farmers in Ogo Oluwa LGA were randomly sampled and information regarding maize production was collected. Multistage sampling method was adopted with the first stage involved the selection of five (5) villages and the second stage involved selecting sixteen(16) respondents from each village, thereby forming a total of eighty (80) respondents and this served as the sample size for that analysis. Both DEA and SFA were used in analyzing the technical efficiency of the maize farmers. The results revealed both descriptive and inferential statistics. The descriptive statistics indicated that mean output per hectare of maize and mean farm size was found to be 613.06kg and 4.17 hectares respectively.

DEA results revealed that the mean technical efficiencies for CRS and VRS were 0.33 and 0.83 respectively and about 11% and 40% of the maize farms were found to be on the production frontier under CRS and VRS respectively. Conversely, the SFA results showed that the Mean Technical efficiencies was 0.66 ,the gamma value was found to be 0.78 or 78% and this means that about 78% of the variations in output were due to disparities in technical efficiencies. Finally, the study also examined the relationship between the two models using spearman's correlation method and the findings indicated that there exists a strong correlation between SFA and DEA models.

Abbas *et al* (2014) estimated congestion in Free Disposal Hull (FDH) models using Data Envelopment Analysis (DEA). The research investigation was done by providing a pair-wise comparison based algorithm in order to assess congestion in the model. Apart from identifying and estimating the source and the amount of congestion, it is also detecting loses of output due to congestion. The model was validated by using some numerical and empirical analysis. No need of any mathematical problems, and hence polynomial algorithm was used to identify congestion in the FDH model.

Daouia and Simar (2003) has extended the work of Aragon *et al* (2000) and Cezal *et al* (2002) and produced a conditional α-Quantile production frontier that is more robust in terms of outliers than the naïve envelopment estimators such as DEA and FDH. This was carried out through the use of probabilistic frame work for efficiency analysis in a multivariate setting. Their study also provided the asymptotic behavior of the α-Quantile with numerical illustrations. The reason for the extension of the α-Quantile to multivariate set up was because there was nonexistence of ordering of Euclidean spaces of dimension greater than one.

Lin and Tseng (2005) used both DEA and SFA methods in measuring the efficiencies of twenty seven (27) international containers ports operations ranging from 1999 to 2002 using single output and three variable inputs. The results revealed outcome of the analysis that average technical efficiency scores of both BCC and CCR under the DEA methods as 0.7075 and 0.6150 respectively. Hong Kong port was found to be technically more efficient and having best performance among the twenty seven international container ports.

3. Research Methodology

3.1. Theoretical Framework

The diagram above indicated the Economic (overall), Technical and Allocative efficiencies as forwarded by Farrell (1957) using two inputs X1 and X2. The production frontier SS' which is convex to the origin O, as seen on the diagram, is called isoquant which simply serves as connecting points that produced the same and equal quantity of outputs using different inputs' combinations. Also observed from the diagram, is a line drawn from point A on Y-axis to point A' on X-axis through point R and cutting SS' at Q'. This particular line is called "iso cost" meaning same or equal expenditure. That is a line joining or connecting points having same or equal cost or prices.

The two inputs (X1 and X2) are transformed in to output during the production process at point P. When the inputs are utilized and output is produced at P, then point P is said to be both technically and allocatively inefficient. This is because when a point not on frontier SS' is said to be technically inefficient. The inefficiency is measured by the distance from Q to P. Therefore, the technical inefficiency is QP/OP. since technically efficient is rated as 1, the Technical efficiency is measured by subtracting QP/OP from 1.

3.2. Theoretical Framework

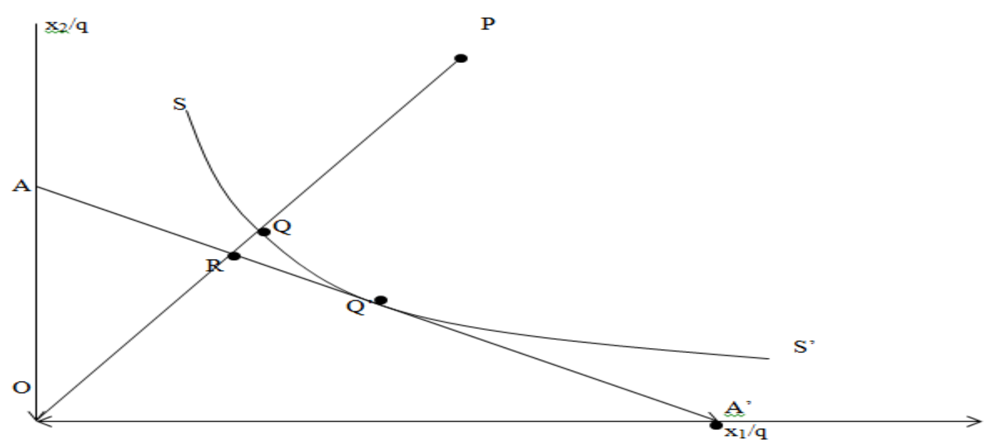

Figure 1: Technical and Allocative efficiency

Source: Coelli *et al*, 2005

Therefore TE= 1-QP/OP =OQ/OP

i.e The technical efficiency can be computed as shown below:

$TE = \frac{OQ}{OP}$ And this is equal to $1 - \frac{QP}{OP}$

The $TE = 1 - \frac{QP}{OP}$

While allocative efficiency is

$AE = \frac{OR}{OQ}$

Since economics efficiency, which is also called overall efficiency, is the product of technical efficiency and Allocative efficiency, therefore;

Economic Efficiency $EE = TE * AE = \frac{OQ}{OP} * \frac{OR}{OQ} = \frac{OR}{OP}$

Therefore, Economic efficiency $EE = \frac{OR}{OP}$

3.3. Data Source

Data were sourced from 307 rubber small holder farmers in five districts of Negeri Sembilan state with 307, 206 and 101 number of smallholder farms under all–age, matured-age and old-age categories respectively. The research data were from both primary and secondary sources. The primary source was through the distribution of structured questionnaires to the respondents, while the secondary data were generated from peer reviewed journals, Malaysian statistics department, books and other reputable articles.

3.4. The Study Area

The study area encompasses five districts which include: Seremban, Tampin, Jempol, Rembau and Kuala Pilah districts. The selection of the districts was based on the proportion of rubber production in the states. Located between Latitude 2° 43' 6.9312N"and Longitude E 101° 56' 56.3564E" north and east of the Equator, Negeri Sembilan is one of the Malaysian 13 States. It is bounded by Kuala Lumpur to the north; to the east is Pahang while its southern neighbors are Melaka and Johor States. It has an average annual temperature of 27.1^{0} C and a mean annual precipitation or rainfall of 1984 mm. The land area was recorded to be around 6,641 square kilometers. The state is well suited for the plantation farming such as oil palm, rubber and coconut plantations. However, rubber and oil palm plantations dominate the agricultural activities in the state. This is because the bulk of plantation productions come from smallholders who cultivate it on a small scale. The name "Negeri Sembilan" which means Nine States composed of nine districts each ruled by a Malay Chieftain.

Below is a comprehensive map of Negeri Sembilan State where the research work was carried out.

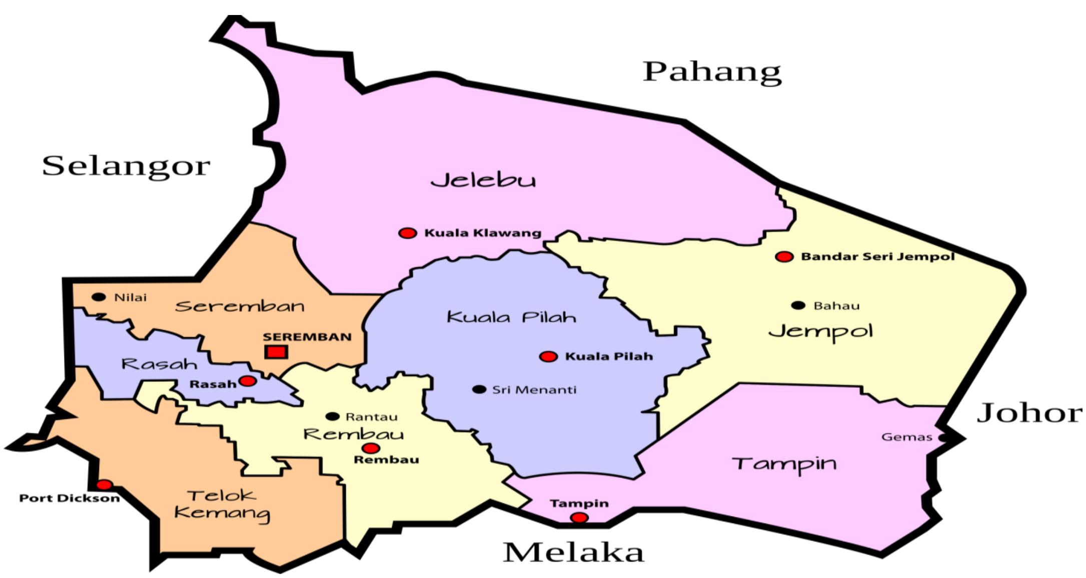

Figure 3: Map of Negeri Sembilan showing Various Districts and towns.

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3.5. Sampling Procedure

A multistage sampling procedure was followed and employed to select rubber growing areas which has high rubber availability and intensity. In the first stage, five (5) rubber producing zones/districts of Seremban, Tampin, Rembau, Kuala Pilah and Jempol districts were selected purposively considering the intensity of rubber area coverage among different districts.

The second stage involved selection of two villages from each of the five districts, making a total of ten (10) villages. The third selection was based on randomly selecting thirty five (35) respondents' farmers from each village, making a total of three hundred and fifty (350) respondents. However, of the three hundred and fifty questionnaires administered, three hundred and thirty eight (338) were returned (retrieved) for a total response rate of 96.6% and of the 338 returned questionnaires; eleven (11) questionnaires were carefully sorted, removed and discarded due to incomplete information or being returned empty. Finally only 327 questionnaires were found to be useful for the research and thus specifically formed the sample size of this study yielding a useable response rate of approximately 97%. The gap created between the numbers of questionnaires collected and the number of useable ones was due to the problem of incomplete responses and statements by some subjects that they were too busy or not interested in participating.

3.6. Cooper Charnes and Rhodes (CCR) or Constant Return to Scale (CRS) MODEL

Inputs, outputs and DMUs were respectively assumed as m, s and n DMUs respectively as expressed below.

$$Max \quad h_k = \frac{\sum_{r=1}^{s} U_r Y_{rk}}{\sum_{r=1}^{m} V_i X_{ik}}$$

$$s.t \quad \frac{\sum_{r=1}^{s} U_r Y_{rj}}{\sum_{r=1}^{m} U_r X_{ij}} \leq 1 \qquad ; j = 1,2, \ldots..n$$

$$U_r, V_i > 0; r = 1,2, \ldots \ldots., s; i = 1,2, \ldots, m;$$

The alphabetical symbols are as defined below, viz:
h_k=is the relative efficiency
$Y_{rj} = r^{th}$ Outputs of the j^{th} DMU;
$X_{rj} = i^{th}$ Inputs of the j^{th} DMU;
U_r is a weight of r^{th} Output
V_r is a weight of i^{th} Input
Under the CCR model, the ration of the maximum weighted output to weighed inputs gives relative efficiency scores (Charnes *et al*, 1978). The above expression or formula has a dual linear programming that can be easily transformed as shown below:

$$Min \qquad h_k = \theta - \varepsilon\left[\sum_{r=1}^{s} S_r^+ + \sum_{i=1}^{m} S_i^-\right]$$

$$s.t \qquad \sum_{j=1}^{n} \lambda_j X_{ij} + S_i^- \le \theta X_{ij}$$

$$\sum_{j=1}^{n} \lambda_j Y_{rj} - S_r^+ \ge Y_{rj}$$

$$\lambda_j \ge 0, S_r^+, S_i^- \ge \varepsilon \ge 0; \forall\, i, r, j$$

$$r = 1, 2, \dots, s; \;\; i = 1,2, \dots\dots, n$$

Where

ε is a positive number

λ_j is a weight of j^{th} DMU;

S_r^+ is a slack variable of r^{th} Output.

S_i^- is a slack variable of i^{th} input.

3.7. Banker Charnes and Cooper (BCC) or Variable Return to Scale (VRS) MODEL

BCC (VRS) MODEL

The restriction of production set placed by CCR model in its assumption of constant return to scale (CRS) has since been replaced and relaxed the restriction by the addition of a convexity restriction by Banker, Charnes and Cooper (BCC) know as BCC model. The Model has DMU assumed to Variable Return to Scale (VRS) with convexity restriction($\sum_{j=1}^{n} \lambda_j = 1$). The BCC model is expressed below.

$$Min \qquad \theta - \varepsilon \sum_{r=1}^{s} S_r^+ + \sum_{r=1}^{m} S_i^-$$

$$s.t \sum_{j=1}^{n} \lambda_j X_{ij} + S_i^- \le \theta X_{ij}$$

$$\sum_{j=1}^{n} \lambda_j Y_{rj} - S_r^+ \ge Y_{rj}$$

$$\sum_{j=1}^{n} \lambda_j = 1$$

$$\lambda_j, S_r^+, S_i^- \ge 0; \forall\, i, r\, j; r = 1,2, \dots., s; i = 1,2, \dots\dots, n$$

3.8. Bootstrapping Technique

The initial idea governing bootstrapping technique as originated and developed dated back in the work of Efron (1979, 1982). These works were then upgraded and improved by Efron and Tibshirani (1993). In these models, the sampling distributions of the data set were approximated using simulation techniques. These ideas were then harnessed and injected in to the field of production frontier by Simar (1996). The first attempt in solving the problem of non-parametric envelopment estimators was achieved by Simar and Wilson (1998). Although, a lot of researches on bootstrapping of efficiency scores have been gaining momentum from that time but a lot of criticism have also been proliferating in the literatures.

Although the basic idea of bootstrap as indicated by Simar and Wilson (2000), that

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$p = p(\Psi, f(x,y))$. Where p is an estimator that helps to generate the original observed data χ_n. If $\hat{P}(\chi_n)$ is a consistent estimator of DGP of p, then $\hat{P}(\chi_n) = \hat{P}(\hat{\Psi}, \hat{f}(x,y)$.
They however advocated that there are two worlds regarding frontier. These are true world and virtual world which often called bootstrap world. It has further indicated that the estimates $\hat{P}, \hat{\Psi}(\chi_n)\ \hat{\theta}_{DEA}(xo, yo)$ In true world

$$\hat{\Psi}^*(\chi_n^*) = \left\{(x,y) \in \mathbb{R}^{p+q} \middle| \begin{array}{l} y \le \sum_{i=1}^n \gamma_i y_i^*; \quad x \ge \sum_{i=1}^n \gamma_i x_i^* \\ \sum_{i=1}^n \gamma_i = 1; \ \gamma_i \ge 0 \forall i = 1 \dots, n \end{array} \right\}$$

For a fixed point $\hat{\theta} *_{DEA} (x_{0,} y_0)$=inf$\{\theta | (\theta_{x_0}, y_0) \in \hat{\Psi}^*\}$,
And by solving the following linear program,

$$\hat{\theta} *_{DEA} (x_{0,} y_0) = min \left\{ \theta > 0 \middle| \begin{array}{l} y_0 \le \sum_{i=1}^n \gamma_i y_i^*; \ \theta_{x_0} \ge \sum_{i=1}^n \gamma_i x_i^* \ ; \\ \sum_{i=1}^n \gamma_i = 1; \quad \gamma_i \ge 0 \forall i = 1., n \end{array} \right\}$$

The estimator $\hat{\theta} *_{DEA} (x_{0,} y_0)$, which is the quantity estimated in the bootstrapped world analogue to $\theta(x_{0,} y_0)$ in the true world, is thus computed. That is by solving the equation above, the estimator is equally solved.

The main relation or link here is, based on the pseudo-sample χ_n^* generated from $\hat{P}(\chi_n)$, $\hat{\theta} *_{DEA} (x_{0,} y_0)$ is an estimator of $\hat{\theta}._{DAE} (x_{0,} y_0)$ in the bootstrapped world; where as within the true world, $\hat{\theta}._{DAE} (x_{0,} y_0)$ is an estimator of $\theta(x_{0,} y_0)$(Simar and Wilson, 2000)
Therefore, if there is consistency in the bootstrap, then the following holds;
$(\hat{\theta} *_{DEA} (x_{0,} y_0) - \hat{\theta}._{DAE} (x_{0,} y_0)) \mid \hat{P}(\chi_n)\ approx(\sim)(\hat{\theta}._{DEA} (x_{0,} y_0) - \theta(x_{0,} y_0)) \mid P.$

3.9. Technical Inefficiency

Below is the truncated –normal distribution of the Technical inefficiency effects (u_i)
(u_i) $=E(u_i|\varepsilon_i) = \frac{\sigma\lambda}{(1+\lambda^2)}\left[\frac{\phi\left(\frac{\varepsilon_i\lambda}{\sigma}\right)}{\Phi\left(-\frac{\varepsilon_i\lambda}{\sigma}\right)} - \left(\frac{\varepsilon_{i\lambda}}{\sigma} + \frac{\mu_i}{\sigma\lambda}\right)\right]$

$\sigma = (\sigma_u^2 + \sigma_v^2)^{1/2}$,$\lambda = \sigma_u/\sigma_v$, $\mu = -\varepsilon_i {\sigma_u^2}/{\sigma^2}$

3.10. Tobit Regression Model

Tobit Regression Model was used to determine the factors influencing technical efficiencies of both the two categories of the rubber smallholders to achieve specific objective v.
EFFij = α0 + α1xij1 + α2xij2 + α3xij3 + α4xij4 + α5xij5 + α6xij6 + α7xij7 + α8xij8+ α9xij9+ α10xij10 + α11xij11 + α12xij12 + eij …………… ix

Where:
EFF = efficiency index for ith farmer (That is efficiencies scores)
α0 = intercept coefficient

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α1 – α16 = parameters estimated

Socioeconomic Factors:

X_1 = Gender

X_2 = Race

X_3 = Marital Status

X_4 = Household size

X_5 = Tapping experience

X_6 = Education level

X_7 = Topography

X_8 = Extension Visits

X_9 = District/location

X_{10} = Farmer's Age

X_{11} = Tapping System

X_{12} = Farm Distance

4. Results and Discussions

This section examined the technical efficiencies of the three age-category crops under both constant returns to scale (CRS) and variable returns to scale (VRS), Bias-Corrected (BC)-VRS and Bias-Corrected(BC) CRS assumptions.

4.1. Technical Efficiency Scores under VRS

Table 2 present the frequencies and percentages corresponding to the range of efficiency scores for the 3 age-category crops of smallholders using data envelopment analysis under variable returns to scale (VRS) assumptions. As previously discussed, all-aged category has sample size of 307, matured-age has 206 and old-age has 101 numbers of smallholders. The mean technical efficiencies of these 3 age categories were computed and found to be 0.95, 0.97 and 0.96 respectively for the all-age, matured-age and old-age categories. This means that only 0.05, 0.04 and 0.03 or 5%, 4% and 3% respectively for all-age, matured-age and old-age categories, are accounted for inefficiency under variable returns to scale assumptions. The table also disclosed that about 153 farms under all-age category are fully technically efficient while 128 and 72 farms were found to be on the frontier under matured-age and old-age categories respectively. In fact, more than 90% of each of the crops-age categories has technical efficiency scores more than 0.8.

Table 2: Technical Efficiency Scores under VRS

Range	All crops	Matured Crops	Old- crops
<-20	0(0.00)	0(0.00)	0(0.00)
0.21-0.30	0(0.00)	0(0.00)	0(0.00)
0.31-0.40	0(0.00)	0(0.00)	0(0.00)
0.41-0.50	0(0.00)	0(0.00)	0(0.00)
0.51-0.60	0(0.00)	0(0.00)	0(0.00)
0.61-0.70	0(0.00)	1(0.49)	0(0.00)
0.71-0.80	10(3.26)	4(1.94)	2(1.98)
0.81-0.90	48(15.64)	25(12.14)	7(6.93)
0.91-0.99	96(31.27)	48(23.30)	20(19.80)

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1	153(48.84)	128(62.14)	72(71.29)
Summary			
Mean	0.95	0.97	0.96
St.Dev	0.06	0.06	0.11
Max	1	1	1
Min	0.74	0.7	0

Source: Field Survey (2015)

Figure 4 below presents a graphical structure of the technical efficiency of the 3 rubber age-categories of all-age, matured-age and old-age categories using Data Envelopment Analysis with Variable return to scale assumptions (VRS). The bars on score range of 1.00 Indicates that all-age; matured-age and old-age categories have more than 140, 120 and 60 farms respectively. There is no single bar on the range of scores from 0.20-0.70. This simply means that the average efficiency score is above 0.90.

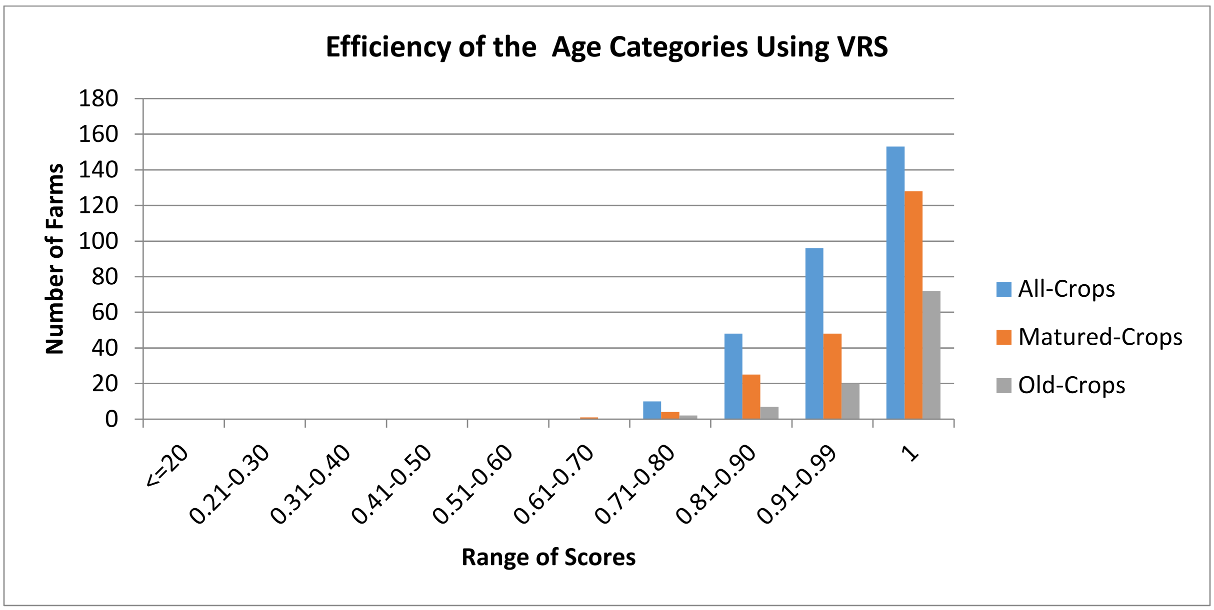

Figure 4: Technical Efficiency of Rubber age categories using VRS.

4.2. Technical Efficiency Scores under CRS

Table 3 presents the results of the range, frequency and percentages of number of rubber smallholders using DEA under constant returns to scale (CRS) assumptions. Unlike in VRS, the mean TE of the 3 age categories under CRS is 0.45, 0.61 and 0.33 for all-age, matured-age and old-age crop categories respectively. Their SD are 0.32, 0.34 and 0.29 in that order. The values of the mean TE of the smallholders are indicating that 65%, 39% and 77% of the all, matured and old crops categories respectively, are accounted for inefficiency. Thus going by this rule, the matured-age category is termed better efficient that the other two age categories. However, the percentage of the farms that are fully technically efficient is slightly higher under old-age category than the matured-age category crops. This is because about 7% of the old-age crop farms are on the production frontier as against only 6% of the matured-age crops farms on the frontier.

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The table also specifically revealed that nearly 70% of the old-age crops are having extremely low efficiency scores as compared to the matured-age crops whose bulk of its farms are between the range of 0.61-0.99. In conclusion, matured-age crops have higher and better efficiency scores, followed by the all-age and then the old-age categories under constant return to scale assumptions.

Table 3: Technical Efficiency Scores under CRS

Range	All crops	Matured Crops	Old- crops
<-20	117(38.11)	53(25.73	48(47.53)
0.21-0.30	21(6.84)	11(5.34)	23(22.77)
0.31-0.40	15(4.89)	3(1.46)	3(2.97)
0.41-0.50	16(5.21)	7(3.40)	4(3.96)
0.51-0.60	13(4.24)	4(1.94)	4(3.96)
0.61-0.70	23(7.49)	11(5.34)	4(3.96)
0.71-0.80	56(18.24)	28(13.59)	3(2.97)
0.81-0.90	26(8.47)	43(20.87)	1(0.99)
0.91-0.99	9(2.93)	35(16.99)	4(3.96)
1	11(3.58)	11(5.34)	7(6.93)
Summary			
Mean	0.45	0.61	0.33
St.Dev	0.32	0.34	0.29
Max	1	1	1
Min	0.05	0.06	0

Source: Field Survey (2015)

The figure 5 presents a bar chart for the 3 age categories of rubber efficiency using the assumption of CRS. The Figure showed that the longest Bars are on the <= 0.20 scale range. Thus this is an indication that majority of the number of crop farms are having very small efficiency scores. For instance, nearly 100 numbers of farms under all-age category have TE scores less than 0.20. The matured-age and old-age categories have about 50 farms each that have less than 0.20 TE scores. However, the Figure also revealed that there are very few number of farms that are technically efficient and are thus found on the production frontier.

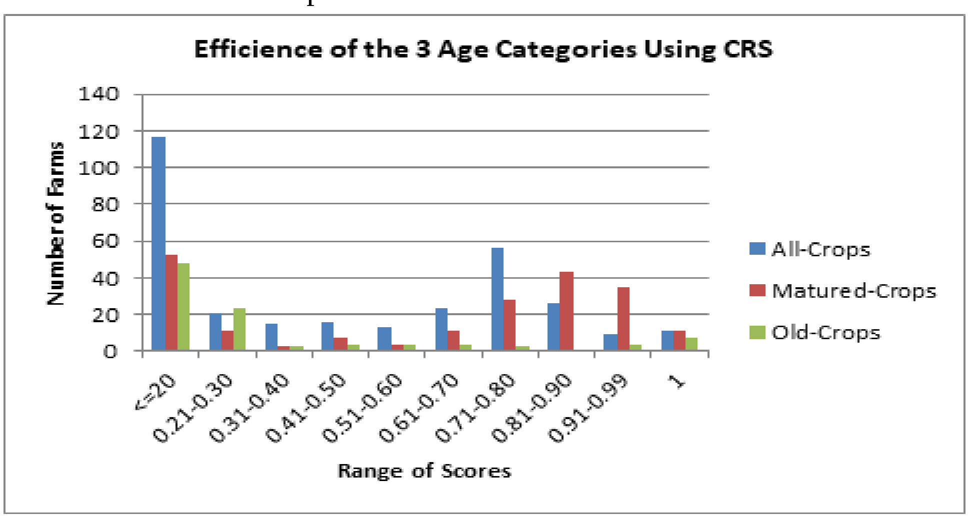

Figure 5: TE of Rubber Age Categories using CRS

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4.3. Bias-Corrected (BC) Scores under VRS

Table 4 presents the range, frequencies and percentages of bias-corrected efficiency scores generated from DEA-bootstrapped of the 3 age-category crops of smallholders under the assumption of variable returns to scale (VRS). The mean bias-corrected technical efficiency scores are 0.94, 0.96 and 0.96 for all-age, matured-age and old-age categories. Their standard deviations are 0.006, 0.006 and 0.005 respectively. The maximum values for each of the age-category crops are 1.00, 1.00 and 1.00 while their corresponding minimum values are 0.73, 0.70 and 0.76 respectively. 72 farms under matured-age crops are on the production frontier while 62 and 37 number of smallholders are on the frontiers of all-age and old-age categories respectively. For the all-age category crops, the larger portion (about 57%) of the farms are between the ranges of 0.91-0.99 scores, while for the matured-age category crops has 48% and the old-age category has approximately 50%. Comparing these bias-corrected efficiency scores with the traditional or naïve DEA, it would be observed that 153, 128 and 72 farms that were fully technically efficient under naïve DEA, has been drastically reduced to 62, 72 and 37 number of farms for all-age, matured-age and old-age categories respectively under bias-corrected . This drastic reduction in the number of technically efficient farms from DEA to bias-corrected (BC) could be attributed to the presence of bias in traditional DEA. This means that naïve DAE is full of bias and thus need to be corrected using bootstrapping techniques to generate and produce bias-corrected technical efficiency scores.

Table 4: Bias Corrected (BC) Scores under VRS

Range	**All crops**	**Matured Crops**	**Old- crops**
<-20	0(0.00)	0(0.00)	0(0.00)
0.21-0.30	0(0.00)	0(0.00)	0(0.00)
0.31-0.40	0(0.00)	0(0.00)	0(0.00)
0.41-0.50	0(0.00)	0(0.00)	0(0.00)
0.51-0.60	0(0.00)	0(0.00)	0(0.00)
0.61-0.70	0(0.00)	1(0.49)	0(0.00)
0.71-0.80	11(3.58)	5(2.43)	2(1.98)
0.81-0.90	58(18.89)	29(14.08)	12(11.88)
0.91-0.99	176(57.33)	99(48.06)	50(49.50)
1	62(20.20)	72(34.95)	37(36.63)
Summary			
Mean	0.94	0.96	0.96
St.Dev	0.06	0.06	0.05
Max	1	1	1
Min	0.73	0.70	0.76

Source: Field survey (2015)

Figure 6 encapsulate a chart of number of farms of each of the all-age, matured-age and old-age categories under BC-VRS assumptions. It is observed that nearly 90% of the bars or number of farms has efficiency scores more than 0.80. About 70 farms belonging to mature-age category are on the production frontier and 60 farms under all-age are on the frontier. The old-age category has nearly 40 farms that are technically efficient.

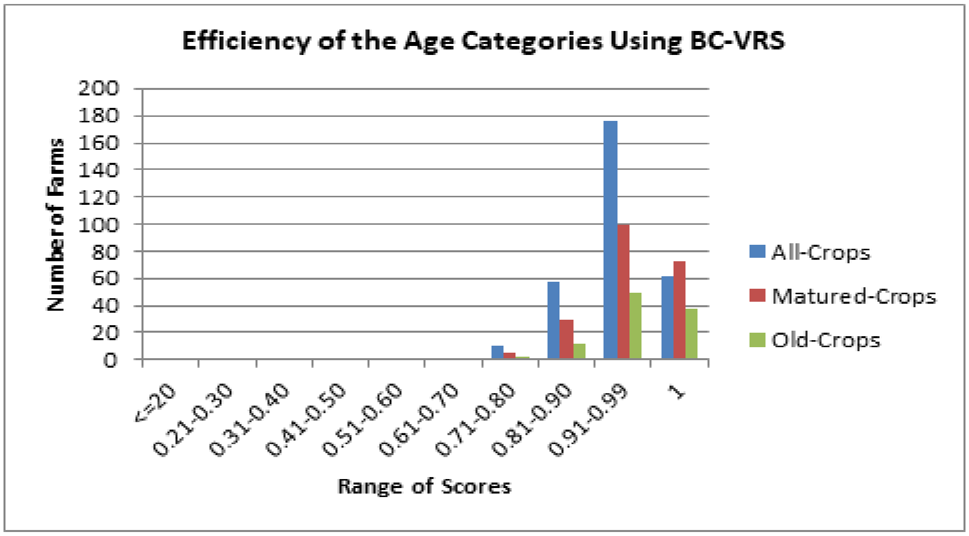

Figure 6: TE of Rubber Age Categories Using BC-VRS.

4.4. Bias-Corrected (BC) Scores under CRS

Table 5 presents the range and frequencies of bootstrapped DEA results for the 3 crop age categories of smallholders under CRS assumptions. The table revealed that there is no single farm that is fully technically efficient .This means that no farm was found on the production frontier of all the 3 different age categories. The mean BC technical efficiency scores for all-age, matured-age and old-age categories are respectively 0.41, 0.58 and 0.25 .Their SD are 0.28, 0.32 and 0.20. Although no single farm was on the production frontiers of all the 3 age categories, however, appreciable number of farms of about 106 was between the range score of 0.71-0.99 under matured-age category. This accounts for more than 50% of the farms under this age category. Under the old-age category, about 72 farms were found to have efficiency scores less than 0.30. The bias-corrected mean technical efficiency score is 0.25 as against its counterpart in traditional DEA which has a slightly higher value of 0.33, a difference of about 8%.

Comparing the Bias-corrected efficiency scores with the traditional DEA scores obtained under CRS assumptions, it would be clearly realized that majority of the farms near the frontier and on the frontier has reduced when bias are removed from naïve DEA using smoothed bootstrapping methods. Also, it would be observed that the number of farms scoring below 0.3 has increased rapidly when bootstrap was applied. This is because removing the bias has increased the number of farms with very low efficiency scores.

Table 5: Bias-corrected (BC) Scores under CRS

Range	All crops	Matured Crops	Old- crops
<-20	123(40.07)	55(26.70)	61(60.40)
0.21-0.30	17(5.54)	8(3.88)	12(11.88)
0.31-0.40	15(4.89)	5(2.43)	6(5.94)
0.41-0.50	20(6.52	6(2.91)	5(4.95)
0.51-0.60	17(5.54)	8(3.88)	4(3.96)
0.61-0.70	44(14.33)	13(6.31)	9(8.91)

0.71-0.80	51(16.61)	33(16.02)	4(3.96)
0.81-0.90	18(5.86)	56(27.19)	0(0.00)
0.91-0.99	2(0.65)	22(10.68)	0(0.00)
1	0(0.00)	0(0.00)	0(0.00)
Summary			
Mean	0.41	0.58	0.25
St.Dev	0.28	0.32	0.20
Max	0.92	0.97	0.74
Min	0.04	0.06	0.08

Source: Field Survey (2015)

Figure 7 expresses the graphical presentation of technical efficiency of the 3 age categories using bias-corrected efficiency with constant returns to scale assumptions. No single bar was found to be on scale range of 1.00. This indicates that there is no technically efficient farm under all the 3 age categories. However, red and blue colour bars are observed on scale range of 0.71-0.80 and 0.81-0.90. The green-colour bar which represents the old-age crop category only appeared on relatively low score ranges from 0.21-0.70. It was also observed that majority of the rubber farms have very low efficiency scores. For instance about 120 farms have scores less than 0.20 under all-age crops. More than 50 farms under each of matured and old-age crops are having less than 0.20 efficiency scores.

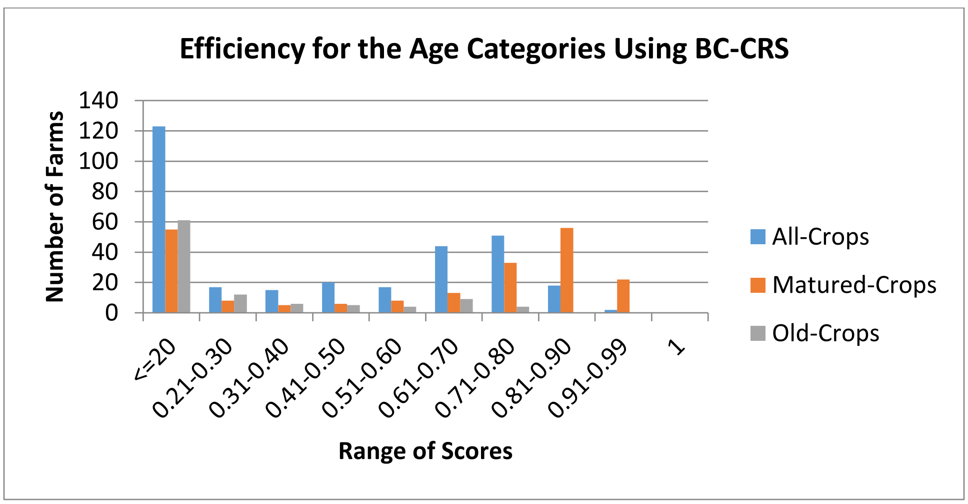

Figure 7: TE of Rubber Age Categories Using BC-CRS.

4.5. Tobit Regression for the 3 Age Categories under VRS Assumptions

Table 6 presents the Tobit regression estimation results of each of the crop-age category of rubber smallholders against the technical efficiency scores under variable returns to scale (VRS) assumptions. Four columns presented in the table labeled as variables, all crops, matured crops and old crops representing the determinant variables used in the study, the coefficients of all-age, matured-age and old-age category of smallholders respectively. The findings of the estimates results revealed that 5 determinants were significant under all-age category crops. Such determinants include educational level, topography, tapping system, farm distance and district of Rembau. The matured-age category has only 3 determinants that have significant influence on the

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technical efficiency scores of the rubber smallholders under variable returns to scale. These significant variables include marital status, tapping system and district of Kuala Pilah. The third category which is the old-age category has six (6) efficiency determinants that are significant and critical in influencing the efficiency of rubber smallholders.

Table 6: Tobit Regression estimates for the 3 categories under VRS assumptions

Variables	**All crops**	**Matured Crops**	**Old- crops**
Gender	0.00	0.00	0.00
Race	0.00	-0.01	-0.01
Marital status	0.00	(-0.02)*	-0.01
family size	0.00	0.00	0.00
Tapping experience	0.00	0.00	(0.00)***
Educational level	(-0.02)**	0.00	(-0.04)***
Topography	(-0.01)**	-0.01	0.00
Extension visits	-0.04	0.01	-0.03
tapping system	(-0.03)***	(-0.03)**	(0.09)***
farmer's age	0.00	0.00	0.00
farm distance	(0.00)***	0.00	0.00
Seremban	0.01	0.03	-0.02
Jempl	-0.01	-0.02	(0.15)***
Rembau	(-0.03)*	-0.03	(0.13)***
Kuala Pilah	0.00	(-0.03)**	(0.18)***
Constant	(1.07)***	(1.03)***	(0.83)***

Source: Field Survey (2015)

Note:
1% level of significance = ***
5% level of significance = **
10% level of significance = *

4.6. Tobit Regression for the 3 Age Categories under BC-VRS Assumptions

The estimates of Tobit regression for the 3 crops age categories of the rubber smallholders, under the assumptions of BC-VRS, are presented in table 7 as shown. The technical efficiency scores of each of the all-age, matured-age and old-age categories were regressed against their respective determinants using methods of Tobit regression analysis. The results of the estimates revealed that factors such as educational level, tapping system and farm distance were significant under all-age category. Statistically significant factors under matured-age category include marital status, tapping system and district of Kuala Pilah; while the old-age category has 8 statistically significant determinants including tapping experience, educational level, extension visit, tapping system, farm distance, districts of Jempol, Rembau and Kuala Pilah. Tapping system was the only factors found to be statistically significant common to all the 3 age categories. The result also showed that educational level and tapping system were negatively significant under all-age category, marital status and tapping system under matured-age category while under old-age category the negatively significant factors are educational level and extension visits. The findings further revealed that other factors also have priori expectations, but are however not significant. Such factors include

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topography, extension visits and districts of Jempol and Rembau under all-age category. Race, districts of Jempol and Rembau under matured-age category while marital status and district of Seremban under old-age category.

Table 7: Tobit Regression for the 3 categories under BC-VRS assumptions

Variables (Bc-vrs)	All crops	Matured Crops	Old- crops
Gender	0.00	0.00	0.00
Race	0.01	-0.01	0.00
Marital status	0.00	(-0.03)**	-0.01
family size	0.00	0.00	0.00
Tapping experience	0.00	0.00	(0.00)***
Educational level	(-0.02)***	0.00	(-0.02)**
Topography	-0.01	0.00	0.01
Extension visits	-0.03	0.01	(-0.03)*
tapping system	(-0.03)***	(-0.02)**	(0.1)***
farmer's age	0.00	0.00	0.00
farm distance	(0.00)***	0.00	(0.00)*
Seremban	0.01	0.03	-0.02
Jempol	-0.01	-0.01	(0.15)***
Rembau	-0.02	-0.02	(0.12)***
Kuala Pilah	0.01	(-0.03)*	(0.16)***
Constant	(1.04)***	(1.01)***	(0.77)***

Source: Field Survey (2015)

Note:
1% level of significance = ***
5% level of significance = **
10% level of significance = *

4.7. Tobit Regression for the 3 Age Categories under CRS Assumptions

Table 8 presents the coefficients of the 15 factors influencing the technical efficiency scores of rubber smallholders, for each of the all-age, matured-age and old-age categories under the assumption of constant return to scale. The revelation from the Table indicated that marital status, tapping system, farm's distance, and districts of Rembau and Kuala Pilah are more critical under all-age category and this means they are in conformity with priori expectations. The matured-age category has marital status, tapping system and district of Kuala Pilah as the most critical factors influencing efficiency of rubber smallholders. The critical factors or determinants under old-age category are race, topography, farm's distance and district of Rembau. Other factors that are in commensurate with theoretical expectations but are however not significant, include gender, topography and district of Seremban under all-age category; while factors such as gender, topography and district of Rembau under matured-age category. The factors under the old-age category include marital status, family size, extension visits, districts of Seremban and Kuala Pilah.

Elaborating on the negatively and statistically significant factors, it would be observed that about 0.14 scores or 14% increases in TE would be achieved when smallholders are married, while

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adopting S/2/d2 tapping system, would lead to an increase in TE scores by 0.11 or11% under all-age category; and only 0.01 or 1% increase in TE when farm distance is extended by a single unit under all-age category. Situations such as married smallholders and adoption of S2/d2 tapping system will increase TE scores by approximately 0.16(16%) and 0.20(20%) respectively under matured-age category. Finally, more Malay smallholders and siting rubber farms on hilly lands would increase TE scores by 0.58(58%) and 0.1(10%) respectively under old-age categories.

Table 8: Tobit Regression estimates for the 3 categories under (CRS) assumptions

Variables	All crops	Matured Crops	Old- crops
Gender	-0.04	-0.06	0.00
Race	0.06	0.02	-0.58***
Marital status	-0.14***	-0.16***	-0.16
family size	0.01	0.00	-0.01
Tapping experience	0.00	0.01***	0.00
Educational level	0.04	0.16***	0.07
Topography	-0.05	-0.02	-0.10***
Extension visits	0.16	0.54***	-0.03
tapping system	-0.11***	-0.20***	0.36***
farmer's age	0.00	0.00	0.00
farm distance	-0.01***	0.01	-0.01***
Seremban	-0.06	0.02	-0.10
Jempol	0.14***	0.16***	0.22
Rembau	-0.23***	-0.14	-0.38***
Kuala Pilah	-0.22***	-0.33***	-0.28
Constant	0.41***	0.05	0.88***

Source: Field Survey (2015)

Note:
1% level of significance = ***
5% level of significance = **
10% level of significance = *

4.8. Tobit Regression for the 3 Age Categories under BC-CRS Assumptions

Table 9 captured the estimated results of Tobit regression of the 3 age-categories of rubber smallholders under the assumption of bias-corrected constant returns to scale. Specifically, the technical efficiency scores generated from bootstrapping DEA under CRS's assumption were used and regressed against the 15 determining the socio-demographic factors of the smallholders. The findings of the results indicated that 6, 7 and 3 determinants respectively under all-age, matured-age and old-age categories were found to be statistically different from zero. When carefully observed these outcomes are virtually very similar to the results under CRS assumption presented in table 4.23. This is an indication that, regardless of conducting bootstrapped DEA, the factors affecting efficiency or determining efficiency would be the same, thus conclusively; bootstrapping has little or no effect on influencing the determinants of efficiency.

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Table 9: Tobit Regression estimates for the 3 categories under BC-CRS assumption

Variables (BC-CRS)	All crops	Matured Crops	Old- crops
Gender	-0.03	-0.05	-0.01
Race	0.06	0.02	-0.24**
Marital status	-0.12***	-0.14**	-0.13
family size	0.01	0.00	0.00
Tapping experience	0.00	0.01***	0.00
Educational level	0.03	0.16***	0.04
Topography	-0.04	-0.03	-0.04
Extension visits	0.12	0.50**	0.03
tapping system	-0.08*	-0.17***	0.21
farmer's age	0.00	0.00	0.00
farm distance	-0.01**	0.01	-0.01***
Seremban	-0.05	0.06	0.02
Jempol	0.14**	0.22***	0.19
Rembau	-0.20***	-0.08	-0.23**
Kuala Pilah	-0.19***	-0.23***	-0.18
Constant	0.36**	-0.04	0.42

Source: Field Survey (2015)

Note:
1% level of significance = ***
5% level of significance = **
10% level of significance = *

5. Conclusions

The study concludes that smallholders with matured-age category crops produced highest mean technical efficiency scores in comparison to the other age-categories such as All-age and Old-age crop categories, under virtually all the techniques including VRS, CRS, BC-VRS and BC-CRS techniques. The implication is that more quantities of rubber are produced under the matured age-category than the other two age-category crops. Therefore, more emphasis needs to be given in terms of policy formulations towards increasing the production of rubber when the plants are under matured-age category. However, in terms of the percentage number of crop farms on the production frontier, old-age category takes the precedence, meaning the old-age category has higher number of farms that were fully technically efficient. Also observed in the study is the importance of bootstrapping techniques in DEA towards overcoming the sensitivity and the bias of the efficiency scores were indicated by the significant difference in TE scores estimated by BC-TE Scores generated from Bootstrapped-DEA. That means bias from conventional or naive DEA was extracted via bootstrapping technique and this improves the quality of the efficiency scores.

With regards to factors affecting efficiency scores, it has been observed that the number of variables found to be significant under conventional DEA for both the CRS and VRS assumptions were virtually the same with their counterparts under the bootstrapped DEA. This means that the significant variables regressed against the naïve DEA scores are the same when regressed against the bias-corrected efficiency scores. Therefore, the implication we can deduce from here is that bootstrapping techniques has no or little effect on the influence of efficiency determinants.

The study further concludes that since matured plantations have the highest mean TE of rubber, then it should be managed agronomically well to increase production and income of smallholders. The difference in TE between the matured-age category and the other two age-categories is also an indication that there is a disparity or an appreciable difference between the aggregated data and disaggregated data. This difference could possibly be attributed to the presence of bias in the wholesome or aggregated data. Thus, we can also conclude that there is a bias in aggregated data on perennial crops and can thus be removed if the data are disaggregated before embarking on full analysis. It is therefore recommended that efficiency measurement should be done on disaggregated form when measuring performance of perennial crops, to eliminate bias.

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