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Comparative Estimation of Technical Efficiency in Livestock-Oil Palm Integration in Johor, Malaysia: Evidence from Full and Partial Frontier Estimators

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Abstract

Two full frontiers (DEA and FDH) and two partial frontiers (order-alpha and order-m) were employed on the same data set for comparative estimation of technical efficiency in the goat-oil palm and cattle-oil palm integration systems. Data were collected from 255 livestock-oil palm integrated smallholder farms in Johor, Malaysia for the 2011 production season. Although the estimators differ in their assumptions but the technical efficiency estimates from the four distinct estimators based on the data set used appear to be similar both in magnitude and distribution as most farms produce either on the frontier or very close to the frontier. The small nature of the farms accounts for the negligible inefficiency recorded; as recommendation, larger farm size is indeed a policy tool that can guarantee frontier production to all farms.

Keywords: order-alpha, order-m, FFB, frontier, FDH

1. Introduction

Although oil palm crop originated from West Africa, its production has long crossed the shores of Africa. Substantial evidence abound not only to attest the production of oil palm outside the horizons of Africa but also to testify the long shift in its global index of production to the Asian continent. Global account for oil palm as a crop will be incomplete without mentioning the role Malaysia played and still playing in transforming the crop to a more economically viable status. Hardly is there any country in the world that invested so much on oil palm both in its up-stream and down-stream activities like Malaysia and hardly also is there a nation in the world that reaped so much economic benefit from oil palm like Malaysia. Malaysia surpassed Nigeria as the world leading producer nation in the 1970s up until Indonesia transcended Malaysia as the highest producer nation in 2007. Today, Malaysia is the second largest producer and highest exporter accounting for 44% of global exports (MPOC, 2013).

Considering the depletion in Malaysia's agricultural land owing to so much land devoted for the oil palm industry and the poor performance of the ruminant sector, there is the need for viable management strategies in the system. Strategies such as integration with livestock and further genetic modifications are avenues that guarantee FFB increase and livestock growth that can help Malaysia remain competitive in the future. Hence, this research focused on the estimation of production efficiency under both goat-oil palm and cattle-oil palm integration system with the view to dispel the aforementioned scenarios. Most efficiency studies on oil palm were estimated under sole production system and full frontier estimation techniques were mostly used. However, this research had ventured into integrated system and applied a combination of both full and partial frontiers to study the effect on the data set along methodological lines. Hence, this study used four approaches of estimating technical efficiency: two full frontiers (DEA and FDH) and two partial frontiers (order-alpha and order-m) on the same data set with a view to study if variations may exist in the efficiency scores they produce.

2. Methodology

2.1 Data Collection

Data collection for this study was cross sectional in nature, obtained from farmers integrating both goat-oil palm and cattle-oil palm in Batu Pahat, Johor Bahru, Kluang, Kota Tinggi, Kulaijaya, Ledang, Mersing, Muar, Pontian and Segamat districts of Johor State, Malaysia. Data collection basically covered production data for the year 2011 (January-December) and collection spanned between January and August, 2012. After outlier test and elimination, data on 255 sample size (plantations) were used for the analyses of this study. The study used a combination of FEAR 1.15 software developed by in 2010 on a 32-bit R version 2.14.0 and DEAP software developed by Coelli for its estimation. The FEAR estimates both the Farrell's and Sheppard's distance function; in this study, the input orientation of the Farrell's convention was used for all estimations; note the Farrell and Sheppard distance function are reciprocal of one another. The two full frontier estimators (DEA and FDH) and the two partial frontier estimators (order-m and order-α) applied in this research was to compare the application of four methodologies on the same data set with the view to understand whether or not exist any variability in the efficiency scores and why?

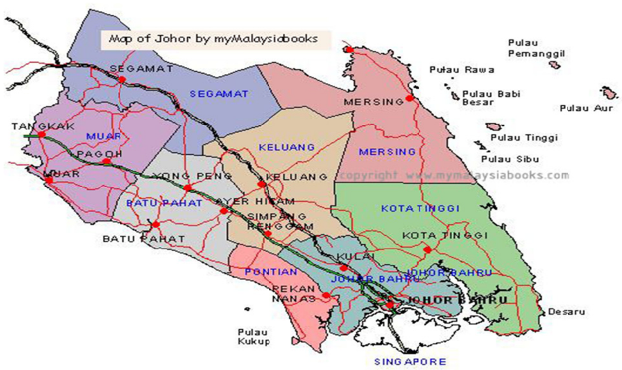

Figure 1. Map of the study area (Johor, Malaysia) according to districts considered during the research

Source: Malaysia books (2012).

2.2 Analytical Techniques: DEA Estimator

Following the existence of an underlying production, technical efficiency in DEA estimator can be estimated. If n represents samples of firm's observations that uses inputs k to produce outputs m, then, X_{ki} and Y_{mi} represents inputs and outputs vectors for the i[th] firm respectively. For firm using a firm utilizing X_{ki} to yield Y_{mi}, the input-oriented technical efficiency is based on CRS assumption as follows: In line with Abatania et al. (2012), technical efficiency can be empirically estimated as below:

$$TE_i(X_{ki}, Y_{mi}) = \min_{\theta,Z} \theta_i\,, (\theta: X_{ki}, Y_{mi})$$

$$subject\ to \begin{Bmatrix} y_{mi} \leq \sum_{i=1}^{I} Z_i y_{mi,}\, m = 1,2,\ldots,m, \\ \sum_{i=1}^{I} Z_i x_{ki,} \leq \theta x_{ki,}\ k = 1,2,\ldots,k, \\ Z_i \geq 0, i = 1,2,\ldots,I, \end{Bmatrix}$$

Where: θ_i= technical efficiency of estimates calculated for each firm i, y_{mi} =quantity produced of output m by firm i , Z_i = denote intensity variable for firm $i.$ A firm is adjudged technically efficient if $\theta = 1$, firms with values of $\theta < 1$ are considered technically inefficient. Note, being a CRS model in the above equation, it implies that all the firms operate at optimum level of production production (Mugera & Featherstone, 2008). However, in agricultural production rarely do we find all farms operating under CRS due to serial imperfections in agriculture. Therefore, additional constraints below are imposed to connote that farmers can as well produce under variable returns to scale (VRS) and non-increasing returns to scale (NIRTS). Thus, $VRS\ constraint \rightarrow \sum_{i=1}^{I} Z_i = 1$and $NIRTS\ constraint \rightarrow \sum_{i=1}^{I} Z_i < 1$.

2.3 Estimation of Technical Efficiency

Amor and Muller (2010) defined technical efficiency in production as the ability of firms to produce maximum output given a set of inputs and technology while technical inefficiency relates to the failure to attain highest possible level of output given input and technology. Technical efficiency range between 0 and 1, a TE = 1 implies technically efficient production (on the frontier) while TE < 1 implies varying degrees of technical inefficiency (Vu, 2010).

$$TE_j = \underset{\theta_j^{CRS},\ x}{Min} \theta_j^{CRS}$$

$$\theta_j^{CRS} X_i > X\lambda$$

$$\lambda \geq 0$$

Where: X = Input vector, Y = Output vector, θ_j^{CRS} = Technical efficiency of farm j under CRS.

2.4 Estimation of Scale Efficiency

Scale efficiency is estimated by taking the ratio of the two efficiencies measured above where scale efficiecy also lie between 0 and 1 (0≤SE≤1). SE = 1 implies efficient economy of scale, SE<1 implies that inputs are not scale efficient which can be a case of either increasing or decreasing returns to scale.

$$SE_j = \frac{\theta_j^{CRS}}{\theta_j^{VRS}} = \frac{TE_j}{EE_j}$$

Where: θ_j^{CRS}= Technical Efficiency under CRS and θ_j^{VRS}= Technical Efficiency under VRS.

However, Vu (2010) stated that the scale efficiency can also decompose farms with scale inefficiency into either increasing returns to scale (IRS) or decreasing returns to scale (DRS) simply by imposing a non-increasing returns to scale (NIRS) to the DEA by adding another convexity constraint ($\sum_{j=i}^{n} \lambda_j \leq 1$) to the to the first TE equation.

$$TE_j = \theta_j^{NIRS} = \underset{\theta_j^{CRS},\ x}{Min} \theta_j^{CRS} + \sum_{j=i}^{n} \lambda_j$$

Where: $\sum_{j=i}^{n} \lambda_j \leq 1$, θ_j^{NIRS}= Technical Efficiency under non-increasing returns to scale and other variables as defined earlier.

The decision rules are: if $\theta_j^{NIRS} = \theta_j^{VRS}$ and SE_j<1, the farm is operating with decreasing returns to scale (DRS) otherwise increasing returns to scale (IRS) if $\theta_j^{NIRS} < \theta_j^{VRS}$

2.5 Free Disposal Hull (FDH) Estimator

The FDH estimator was introduced by Deprins et al. (1984), which is both a deterministic and non-parametric tool for measuring productive efficiency. It is deterministic due to its inability to accommodate stochastic properties, its non- parametric nature arise from its lack of functional form specification. Like the DEA estimator, the FDH is also very sensitive to outliers/ extreme observations, susceptible to dimensionality problems and highly sensitive to noise. However, the FDH and the DEA estimators differ substantially in that the DEA estimators assumes convex nature of production relationship; in the FDH such assumption is relaxed, thus no convexity is assumed.

2.6 Derivation of FDH Estimator

The derivation of FDH presented here is in line with De Borger et al. (1994). Suppose $y = y(y_1, y_2, \ldots, y_n)$ denote n non-negative outputs produced by utilizing numerous m non-negative inputs $X = X(X_1, X_2, \ldots, X_n)$ combination. Thus, the production possibility set Yrefers to the set of all combinations of inputs and outputs that are technically feasible, as shown below:

$$Y = \{(x, y) | x \in R_+^n, y \in R_+^n, (x, y) is\ feasible\ \}$$

Conveniently, the production technology can be modeled by an input correspondence$y \rightarrow L(y) \subseteq R_+^n$. For a specific vector of output y, the level set $L(y)$ represents the subject of all input vectors X that produce a minimum of the output vector y. Various production technologies can be defined by subjecting the level set $L(y)$ to various restrictions. While there may be some variations in the non-parametric estimators, regarding imposition of restrictions or assumptions, but generally they are less restrictive or have very weak assumptions than the parametric approaches. FDH estimator can be defined by the axioms below:

$$0 \notin L(y)\ for\ y \geq 0, and\ L(0) = R_+^n \quad \text{Axiom 1}$$

Axiom 1 assumes that it is not possible to obtain semi positive output from a null input vector. Thus, no such thing as free production and that any non-negative input yields a minimum of zero level of output.

$$if\ \parallel y^l \parallel \to +\infty\ as\ l \to +\infty, then\ \cap_{l=1}^{+\infty} L(y^l)\ is\ empty \quad \text{Axiom 2}$$

Axiom 2 states that for any utilization of finite inputs, finite outputs are produced.

$$if\ x \in L(y) and\ x' \geq x, then\ x' \in L(y) \quad \text{Axiom 3}$$

Axiom 3 is called positive monotonicity or strong free disposability of inputs; implying that an increase in input *x* cannot lead to a decrease in output *y*.

$$L(y)\ is\ a\ closed\ correspondence \quad \text{Axiom 4}$$

The closedness axiom 4; states that an array of input vectors can each yield output bundle y and converge to x^*, then the same x^*can also yield output bundle *y*.

$$if\ y' \geq y, then\ L(y') \subseteq L(y) \quad \text{Axiom 5}$$

The last axiom (strong free disposability of output) provides for variable returns to scale and assumes any reduction in output bundles remain producible with the same quantity of input bundles. The specification of the FDH input correspondence is thus:

$$L(y)^{FDH} = \{x | x \in R_+^m, Z'N \geq y, Z'M \leq x, I_k'Z = |Z_i \in \{0,1\}\}$$

Where N represents kxn matrix of observed outputs, M represents kx1vector of intensity and I_k represents kx1 vector of ones. Hence, it is obvious that the axioms did not impose convexity assumption on the technology. Using the axioms, the specification of FDH output correspondence can be given as below:

$$P(x)^{FDH} = \{y | y \in R_+^n, Z'N \geq y, Z'M \leq x, I_k'Z = |, Z_i \in \{0,1\}\}$$

From the last two equations, the FDH graph correspondence can finally be defined with respect to either input or output correspondence as follows:

$$GR^{FDH} = \{(x,y) | x \in L(y)^{FDH}, x \in R_+^m, y \in R_+^n\}$$
$$= \{(x,y) | y \in P(x)^{FDH}, x \in R_+^m, y \in R_+^n\}$$

2.7 Order-alpha (α) Estimator

Order-alpha (α) is a generalization of the FDH estimator but in a different manner. While the FDH uses the concept of minimum input consumption among available peers for benchmarking, the order-α employs the $(100\text{-}\alpha)^{th}$ percentile approach (Tauchmann, 2011).

$$\hat{\theta}_{\alpha i}^{oA} = \underset{j \in B_i}{P(100-\alpha)} \left\{ \max_{k=1,\dots,k} \left\{ \frac{x_{kj}}{x_{ki}} \right\} \right\}$$

If α =100, both order-α and FDH gives the same output, while for values of α<100, some super-efficient firms may result and un-enveloped by the estimated production possibility frontier. The α is to order-α estimator what *m* is to order-m estimator; thus a decision (tuning) parameter that influence the output of the estimator.

2.8 Order-M Estimator

The order-m estimator is another non-convex and non-parametric estimator that is known for its important property of achieving root-n ($\sqrt{n}$) consistency that aid the estimator to circumvent the problem of dimensionality associated with the traditional non-parametric estimators such as the DEA. Using the order-m estimator to estimate $\mathcal{P}^{\partial t}$ will alter the root-n consistency property by losing it completely, to maintain the property, $\mathcal{P}_m^{\partial t}$ should be estimated instead. Order-m estimator provides robust estimates in relation with noise and outliers in the data set; for finite m, order-m estimates are more robust than DEA or FDH estimators and as m tend to infinity (∞), the order-m estimator converges to FDH estimator (Wheelock & Wilson, 2003).

2.9 Derivation for Order-M Estimator

Order-m is estimated based on expected maximum output frontiers; this helps to relax the convexity assumption and allow for noise (with zero expected value) in the output measures (Wheelock & Wilson, 2003). Remember, that the density $\mathfrak{f}^t(x,y)$ exerts bounded support on the production set $\mathcal{P}^t$. Then, the conditional distribution function for the density $\mathfrak{f}^t(x,y) is\ \mathbb{F}^t_{y/x}(y_0|x_0) = \mathbb{P}_r(y \le y_0 | x \le x_0)$. Given level of inputs x_0 within the region of *x* and considering *miid* random variables $\{V_j\}^m_{j=1,} V_j \in \mathbb{R}^q_+$, drawn from the earlier stated conditional distribution $\mathbb{F}^t_{y/x}(\cdot\,|x_0)$, define the set as below:

$$\mathcal{A}^t_m(x_0) = \left\{(x,y) \in \mathbb{R}^{p+q}_+ | x \le x_0, \quad \bigcup_{j=1}^{m} y \le \mathbb{V}_j\right\}$$

Where $\mathcal{A}^t_m(x_0)$ is random and depends on the specific draw of m vectors from the conditional distribution $\mathbb{F}^t_{y/x}(\cdot\,|x_0)$. To define the random distance function, see below:

$$\mathbb{D}\left(x,y|\mathcal{A}^t_m(x)\right) \equiv inf\{\theta > 0 | (x, y/\theta) \in \mathcal{A}^t_m(x)\}$$

For any value of $y \in \mathbb{R}^q_+$, provides the expected maximum output level of order-m for all values of *x* in order that:

$$\mathfrak{f}^t_x(x) = \mathfrak{f}^t(x,y) | \mathfrak{f}^t\left({}^y/_x\right) > 0 as y^{\partial t}_m(x) \equiv y | \mathbb{E}\left[\mathbb{D}\left(x,y|\mathcal{A}^t_m(x_0)\right)\right]$$

Thus, above is the output-oriented analog of input measure (Cazals et al., 2002). To form the order-m analog of $\mathcal{P}^t$, define as follows:

$$\mathcal{P}^t_m \equiv \left\{(x,y) | (x,y) \in \mathcal{P}^t, y \le y^{\partial t}_m(x)\right\}$$

Above represents expected production set of order-m and finally, we denote of the compliment of $\mathcal{P}^t_m$ as $\mathcal{P}^{\partial t}_m$ and name it the order-m frontier.

To facilitate the understanding of order-m concept, consider (x,y) lying within $\mathcal{P}^t$. The projection of (x,y) onto the frontier $\mathcal{P}^{\partial t}$ is given as $\left(x,y|\mathbb{D}(x,y|\mathcal{P}^t)\right)$, given that the input bundles $x, \mathbb{D}(\mathcal{P}^t)^{-1}$ is the maximum feasible proportionate increase in output bundles, y. Other way, $y^{\partial t}_m(x)$ is the expected maximum output bundle (with equal output proportions as *y*) among *m* firms selected at random, on the condition that their inputs are equal to or less than *x*. Vividly, $y^{\partial t}_m(x) \le y | \mathbb{D}(x,y|\mathcal{P}^t)$, and it can be shown that:

$$lim_{m\to\infty}\, y^{\partial t}_m(x) = y|\mathbb{D}(x,y|\mathcal{P}^t)\ and\ thus\ \mathcal{P}^t_m \to \mathcal{P}^t as\ m \to \infty.$$

Unlike the traditional non-parametric estimators that compares or benchmarks the output of a given firm to the maximum feasible output in the sample, the order-m estimator compares the firm's observed output bundles to what could be expected from any m randomly selected firms that utilize no more input bundles than the given firm.

2.10 Monte Carlo Technique for Order-M Estimator

Cazals et al. (2002) introduced a simple Monte Carlo technique; a simulation method for generating the order-m estimates of $\mathbb{E}\left[\mathbb{D}\left(x,y|\mathcal{A}^t_m(x)\right)\right]$ and hence $y^{\partial t}_m$. The random distance function for a specific draw $\{\mathbb{V}_j\}^m_{j=1}$ can be computed by:

$$\mathbb{D}\left(x,y|\mathcal{A}^t_m(x)\right) = \min_{j=1,\ldots,m}\left[\max_{l=1,\ldots,q}\left(\frac{yl}{v_j l}\right)\right]$$

Where yl and $v_j l$ denote the l^{th} elements of y and v_j implementing the Monte Carlo method requires drawing vitiates v_j from the empirical analog of the conditional distribution earlier stated $\mathbb{F}^t_{y/x}\left({}^{\cdot}/x_0\right)$ as shown below:

$$\widehat{\mathbb{F}}^t_{y/x,n_t}(y_0|x_0) = \frac{\sum_{i=1}^{n_t}\mathbb{I}\left(x_i \le x_0, y_i \le y_0\right)}{\sum_{i=1}^{n_t}\mathbb{I}(x_i \le x_0)}$$

Where $(x_i y_i) \in \varsigma^t_{n_t} \forall\ i = 1,\ldots,n_t$. If $\left(x_0, y_0\right)$ is the point of concern, the steps are as follows:

(i) From the observations in $\varsigma^t_{n_t}$, drawn samples m times, independently and with replacement in order that $x_i \le x_0$; drop the input vectors and denote the sample of the remaining output vectors by $\{\mathbb{V}_{kj}\}^m_{j=1}$.

(ii) Compute $\widetilde{\mathbb{D}}_k\left(x_0, y_0|\varsigma^t_{n_t}, m\right) = \min_{j=1,\ldots,m}\left\{\min_{l=1,\ldots,q}\left(\frac{vk_j l}{yol}\right)\right\}$

(iii) Where $vk_j l$ and yol denotes the l^{th} elements of vk_j and y_0.

(iv) Iterate steps (i)-(ii) *k* times to obtain $\left\{\widetilde{\mathbb{D}}_k\left(x_0, y_0|\varsigma^t_{n_t}, m\right)\right\}^k_{k=1}$

(v) Compute $\widehat{\mathbb{D}}_{m,n_t}\left(x_0,y_0\right) = \widehat{\mathbb{D}}\left(x_0, y_0|\varsigma^t_{n_t}, m\right) = \mathbb{K}^{-1}\sum_{k=1}^{k}\widetilde{\mathbb{D}}_k\left(x_0, y_0|\varsigma^t_{n_t}, m\right)$ and estimator of $\mathbb{E}\left[\mathbb{D}\left(x,y|\mathcal{A}^t_m(x)\right)\right]$. Thus, an estimator $\hat{y}^{\partial t}_{m,n_t}$ of $y^{\partial t}_m$ can be estimated by replacing $\mathbb{E}\left[\mathbb{D}\left(x,y|\mathcal{A}^t_m(x)\right)\right]$ with $\widehat{\mathbb{D}}_{m,n_t}\left(x_0,y_0\right)$.

2.11 Definition of Input and Output Variables

In this study, estimation of efficiency was based on 7 inputs and 2 outputs. The input and output variables are as follows:

X_1 = Farm size (land) (Ha)

X_2= Farm maintenance (RM/yr) (Source: maintenance of roads, paths and bridges and maintenance of farm building)

X_3 = Fertilizer (Kg)

X_4 = Capital (RM/yr) (Sources: land tax, fuel cost for machines, maintenance of machines, tools and equipment, depreciation, establishment cost)

X_5 = Family labor (Man-hour/yr)

X_6 = Hired labor (RM) (Sources: major hired labor operations; harvesting and weeding (land clearing))

X_7 =Other costs (RM) (Sources: salt, brown sugar, palm kernel cake (PKC) medicine, vaccine and supplements)

Y_1=Fresh Fruit Bunches (FFB) yield (MT/yr)

Y_1 =Livestock (Number of stock/yr)

3. Results and Discussion

3.1 Outlier Elimination and Descriptive Statistics of Data Used for the Analyses

Figure II and III show the box and whiskers plots for goat-oil palm and cattle-oil palm integrated farms respectively constructed after outlier elimination in the data set. Note, all the data lies within the box region, none lies outside the box or whiskers region. The outlier elimination process helps to improve the validity or accuracy or robustness of the efficiency estimates.

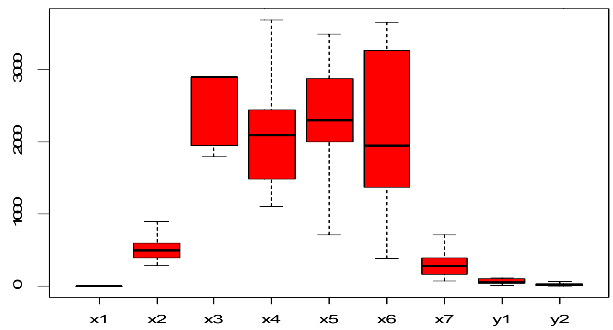

Figure II: Box and Whiskers plots for outlier detection and description of the statistical pattern of the data used for goat-oil palm integration

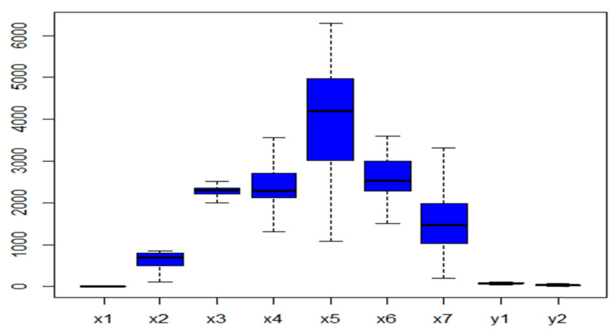

Figure III: Box and Whiskers plots for outlier detection and description of the statistical pattern of the data used for cattle-oil palm integration

Table 1 below also describes the statistical pattern or behavior of the data used for the efficiency analyses under goat-oil palm and cattle-oil palm integration respectively. In terms of farm size, the cattle-oil palm plantations maintain relatively larger farm size relative to the goat-oil palm plantations. The relatively larger farm size of the cattle-oil palm plantations perhaps explains its higher farm maintenance costs relative to goat-oil palm. The same reasoning of large farm size may be adduced for higher capital and hired labor under the cattle-oil palm relative to the goat-oil palm plantations.

Table 1. Descriptive Statistics of data used for both goat-oil palm and cattle-oil palm integration systems

Variable	Definition	Goat-Oil palm integration system				Cattle-Oil palm integration system			
		Minimum	Maximum	Mean	St.Dev.	Minimum	Maximum	Mean	St.Dev.
X1	Land (ha)	1.20	6.00	3.64	1.31	2.50	7.00	4.05	0.41
X2	Farm maintenance (RM/yr) (Sources: maintenance of roads, paths and bridges and maintenance of farm building)	290.00	900.00	510.30	168.21	120.00	850.00	624.70	172.14
X3	Fertilizer (Kg)	1800.00	2900.00	2480.00	480.06	2000.00	2500.00	2293.00	139.345
X4	Capital (RM/yr) (Sources: land tax, fuel cost for machines, maintenance of machines, tools and equipment, depreciation, establishment cost)	1106.00	3700.00	2034.00	649.05	1309.00	3563.00	2414.00	449.20
X5	Family labor (Man-hour/yr)	720.00	3500.00	2412.00	672.30	1080.00	6300.00	3954.00	1005.86
X6	Hired labor (RM) (Sources: major hired labor operations; harvesting and weeding (land clearing))	390.00	3660.00	2135.00	987.09	1500.00	3660.00	2658.00	560.06
X7	Other costs (RM) (Sources: salt, brown sugar, medicine, vaccine and supplements)	75.81	716.00	318.11	176.47	210.00	3312.00	1519.00	631.38
Y1	Fresh Fruit Bunches yield (MT/yr)	10.00	116.00	66.81	32.17	50.00	120.00	88.58	18.67
Y2	Livestock (Number of stock)	2.00	63.00	27.00	6.71	10.00	80.00	40.00	15.17

Source: Field survey (2012).

The farm size index and stocking rate of animals are important in explaining the variation in use of fertilizer, family labor and other costs. For instance, the fact that the cattle-oil palm plantations keep more animals relative to the goat-oil palm plantations in addition to the fact that the cattle deposit more dung than the goat as source of organic manure explains why the cattle-oil palm plantations apply lower levels of inorganic fertilizer in relation to the goat-oil palm plantations. Other source of variation in other costs in addition to farm size and stocking rate is the use of palm kernel cake (PKC) in the cattle-oil palm system while no evidence of it been use in the goat-oil palm system. The fact that 93% of the farmers under cattle-oil palm scheme are from FELDA as against 43% under goat-oil palm system may be the rationale behind higher yield of 88.58MT/yr in former relative to 66.81 MT/yr in the latter.

3.2 Results of Estimation of Technical Efficiency Based on DEA Estimator

Table 2 presents technical efficiency scores disaggregated according to variable returns to scale, constant returns to scale and scale efficiency assumptions under goat-oil palm integration. Overall, the technical efficiency estimates show that all the plantations operate between an efficiency range of 0.958 and 1.000 with a mean score of 0.997. On average all plantations produced at 99.7% efficiency which also translates to 0.3% inefficiency. The mean efficiency estimate implies that under present production technology, goat-oil palm integrated plantations can on average potentially withdraw supply of input by 0.3% and still produce the same level of output bundle. This means that only 0.3% inefficiency level is present; suggesting very low prospects withdrawing the supply of inputs in order to enhance efficiency. The narrow efficiency range observed is an indication that there is no wide variation in yield among the plantations.

Table 2. Technical efficiency estimates disaggregated according to VRS, CRS and SE assumptions across goat-oil palm and cattle-oil palm integration based on DEA estimator

Efficiency range	$TE\text{-}_{VRS}$(PTE)	$TE\text{-}_{CRS}$(OTE)	SE
Goat-oil palm integration (N=65)			
<0.50	0	0	0
0.51-0.60	0	0	0
0.61-0.70	0	0	0
0.71-0.80	0	0	0
0.81-0.90	0	4 (6.15)	4(6.15)
0.91-0.99	10 (15.38)	26 (40.0)	25 (38.46)
1.00	55 (84.62)	35 (53.85)	36 (55.38)
Summary statistics			
Minimum	0.958	0.802	0.802
Maximum	1.000	1.000	1.000
Mean	0.997	0.977	0.979
Standard deviation	0.009	0.039	0.038
Cattle-oil palm integration (N=190)			
<0.50	0	0	0
0.51-0.60	0	0	0
0.61-0.70	0	0	0
0.71-0.80	0	0	0
0.81-0.90	0	0	0
0.91-0.99	0	0	0
1.00	190 (100.00)	190 (100.00)	190 (100.00)
Summary statistics			
Minimum	1.000	1.000	1.000
Maximum	1.000	1.000	1.000
Mean	1.000	1.000	1.000
Standard deviation	0.000	0.000	0.000

Source: Field Survey (2012).

In other words, the plantations seem to operate at relatively uniform yield. In comparison with the table for goat-oil palm integration, the cattle-oil palm integration shows all plantations as ostensibly efficient under all assumptions of VRS, CRS and SE and an average technical efficiency of 1.000 resulted. This means that the present production method and technology provides no room for input withdrawal (reduction) in order to produce the present level of output bundle; thus, suggesting no inefficiency at all. These very high technical efficiency levels estimated under both goat-oil palm and cattle-oil palm integrated systems in Table 2 is not surprising as many of these plantations had won productivity awards in the past and their many years of experience could be an added rationale for high technical efficiency. Other reasons for the high technical efficiency could be the assumption surrounding the DEA estimator; the DEA is not robust to noise (De Witte & Marques, 2010), hence factors beyond farmers' control which cause inefficiency cannot be estimated using the DEA. Based on the foregoing limitations of the DEA, the study explored other efficiency estimators in an attempt to derive robust estimates.

The CRS assumption presents relatively lower estimates which range between 0.802 and 1.000 with a mean of 0.977; suggesting 97.7% efficiency level or 2.3% inefficiency level. These lower estimates under CRS relative to VRS assumption is in consonance with theory as the enveloping surface is tighter under CRS; thus, permitting lower efficiency estimates. Note also the percentage of plantations that attained 100% efficiency reduced from 55% under VRS down to 35% under CRS. The scale efficiency, like the CRS estimates also range between 0.802 and 1.000 with mean of 0.979. Thus, high levels of average scale efficiency, but comparing the scale efficiency scores with the pure technical efficiency (VRS estimates) in line with Padilla and Nuthall (2012), on average the SE (0.802) estimated here is lower than the PTE (0.997). In accordance with Padilla and Nuthall (2009), in the present study the lower value of SE against PTE implies that rather than managerial problems, scale of production or the small nature of farm size appear to be the major cause of inefficiency. Increase in scale of production is indeed an avenue to improving the efficiency in the goat-oil palm integrated system.

3.3 Results of TE Estimation Based on FDH, Order-α and Order-m Estimators

Table 3. Technical efficiency estimates based on FDH, order-alpha and order-m estimators for goat-oil palm and cattle-oil palm integration

Efficiency range	$TE_{FDH\text{-}Estimator}$	$TE_{ORDER\text{-}\alpha\text{-}Estimator}$	$TE_{ORDER\text{-}M\text{-}Estimator(NREP=2000)}$
Goat-oil palm integration (N=65)			
< 0.50	0	0	0
0.51-0.60	0	0	0
0.61-0.70	0	0	0
0.71-0.80	0	0	0
0.81-0.90	0	0	0
0.91-0.99	0	45 (69.23)	38 (58.46)
1.000	65 (100.00)	20 (30.77)	27 (41.54)
Summary			
Min	1.000	0.970	0.941
Max	1.000	1.000	1.000
Mean	1.000	0.998	0.990
Std. Dev.	0.000	0.004	0.016
Cattle-oil palm integration (N=190)			
< 0.50	0	0	0
0.51-0.60	0	0	0
0.61-0.70	0	0	0
0.71-0.80	0	0	0
0.81-0.90	0	0	10 (5.26)
0.91-0.99	0	170 (89.47)	142 (74.74)
1.000	190 (100.00)	20 (30.77)	38 (20.00)
Summary			
Min	1.000	0.910	0.853
Max	1.000	1.000	1.000
Mean	1.000	0.998	0.972
Std. Dev.	0.000	0.008	0.033

Source: Field Survey (2012).

Table 3 captures technical efficiency estimates based on three (FDH, order-α and order-m) estimators for goat-oil palm integrated plantations. The FDH estimator shows that all plantations are fully efficient (100%) showing no potentiality for inefficiency. This result is expected since unlike the DEA, the FDH estimator relaxes the convexity assumption and hence results to higher estimates relative to the DEA estimator. Similar result of 100% average efficiency was also estimated under the cattle-oil palm integrated plantations. Several studies such as De Borger et al. (1994) and De Witte and Marques (2010) that compared FDH and DEA estimators on the same data set reported higher FDH estimates as against the DEA estimates, purely due to the difference in convexity assumption.

In terms of order-α estimator, based on α-value = 0.95, under goat-oil palm integration shows estimates of 0.970, 1.000 and 0.998 as minimum, maximum and mean efficiency estimates respectively. This 99.8% level of average efficiency further implies only 0.2% inefficiency level to be adjusted. The result of mean efficiency under the goat-oil palm integrated plantation is consistent with that of cattle-oil palm integrated plantations; 0.910, 1.000 and 0.998 for minimum, maximum and mean scores were estimated. The order-m estimates allowing for 2000 bootstrap iteration for goat-oil palm system provided 0.941, 1.000 and 0.990 as estimates for minimum, maximum and average efficiency scores. Similarly, the order-m estimates under cattle-oil palm integration estimated in the table were 0.853, 1.000 and 0.972 as minimum, maximum and mean efficiency scores respectively. Comparing the results of TE scores under the four estimators (DEA, FDH, order-α and order-m), it can be observed that the mean scores did not vary much across the four estimators and under both goat and cattle integrated plantations. Results presented above all concur that under both goat and cattle integrated with oil palm, optimal production results and under both systems, farmers produce with less inefficiency level. Note that TE scores estimated under the partial estimators show lower values relative to those predicted by the full estimators. Thus, the full estimators show higher level of inefficiency relative to the partial estimators. This is not surprising considering the assumptions surrounding the partial estimators, which embeds some degree of bias associated with agricultural production that gives a proportion of factors beyond farmers control in its estimation aside the inefficiency itself. The foregoing attributes is not inherent in full frontier estimators, hence the relatively higher TE estimates.

4. Conclusions

The study revealed that the livestock-oil-palm integrated farms either operate close to the frontier or on the frontier; suggesting viable enterprise combination. The mean efficiency estimate implies that under present production technology, goat-oil palm integrated plantations can on average potentially withdraw supply of input by 0.3%, 0.0%, 0.2% and 1.0% under DEA, FDH, order-α and order-*m* estimators respectively and still produce the same level of output bundle. Similarly, the cattle-oil palm integrated plantations can on average potentially withdraw input supply by 0.0%, 0.0%, 0.2% and 2.8% under DEA, FDH, order-α and order-*m* estimators respectively and still produce the same level of output bundle. This in general connotes that livestock-oil palm integration is an optimal system of agricultural production and the farmers produce with minimal inefficiency level.

Based on the mean comparison in this study across the four estimators, it revealed a non-significant statistical difference in mean TE across the estimators used. However, relative to the nature of data used in this study, the FDH and the DEA estimators seem to show better result but in terms of capturing bias associated with agricultural production, the order-m and order-α are more suitable. The study also found small scale of farm operation as the main cause of inefficiency and suggested increase in farm size as medium for improving efficiency in the livestock-oil palm integration system.

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