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Homogenous Smoothed Dea-Bootstrap Optimization of Robust Technical Efficiency in Livestock-Oilpalm Integration in Johor, Malaysia

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Abstract: A homogenous smoothed DEA-bootstrap estimator a simulation method set with 2000 bootstrap iterations was employed to optimize robust technical efficiency and its determinants in goat-oil palm and cattle-oil palm integrated plantations under smallholder scheme using 255 plantations drawn from 10 districts of Johor, Malaysia. Box and whiskers plots were conducted for outlier detection and hence, extreme observations were eliminated in the data set. The study disaggregated production inefficiency from noise via bias estimation which captures exogenous factors beyond farmers control such as climate, policy shocks, flood, torrential rainfall, disease and others. Result show higher bias-corrected technical efficiency and lower bias estimate in the cattle-oil palm relative to the goat-oil palm integration, thus the cattle-oil palm system was adjudged a better system than the goat-oil palm integration. All plantations operate under sub-optimal level and increasing returns to scale rather than poor management, the small farm size nature of the plantations was adjudged as the main cause of inefficiency. Age, education, years of integration, extension visit and credit has shown positive and significant relationship with technical efficiency. Policy decision encouraging increased farm size and one that can mitigate the effect of some detrimental exogenous factors will help increase their efficiency status.

Key words: Bias, bootstrap, iteration, noise, simulation

INTRODUCTION

Malaysia has for many decades been recognized as a global giant in the vanguard of palm oil production, processing, exports, research and innovations to meet the goals of increased productivity, enhanced efficiency and provision of better income to the farming families in addition to foreign exchange earnings. The livestock industry is equally another important nerve to the Malaysian economy but unlike the oil palm sub-sector that contributes substantially to the agricultural sector performance and indeed the overall economy, employs millions in labour force and engage in trade relations to hundreds of countries worldwide, the livestock sub-sector accounts for very minimal share to the agricultural sector performance in spite of the surge in demand for beef concomitant with the population influx. The oil palm industry has earned the Malaysian economy RM80.4 billion (USD 26.8 billion) in 2011 alone and employs millions both in skilled and un-skilled labour (MBOB, 2012) while the livestock industry as a whole managed to contribute only an average of 2% to the GDP (Serin *et al*., 2008). Furthermore, Mohamed (2012) attested that the Malaysian beef industry is inefficient and lacks comparative advantage and as at 2010, Malaysia achieved only 28.89 and 4% self-sufficiency level in beef and milk production respectively (DVS, 2010). Despite the significance of the oil palm industry in Malaysia, the policy of economy of scale had led to shortage of land, coupled with land underutilization and the shortage of labour force contributes to higher cost of FFB production. Thus, a symbiotic system, beneficial to both parties such as livestock integration that could help tap the benefits of economy of scope, aid break the jinx in high cost of production, stimulate the growth of local beef sub-sector and increase intensity of land use maximization is quite worthy and timely. Hence, this study assessed oil palm integration under two categorical systems: Cattle-oil palm and goat-oil palm integration with respect to analyzing production efficiency and factors influencing it.

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MATERIALS AND METHODS

The DEA-bootstrap: DEA-bootstrap, an efficiency estimator which was introduced by Simar and Wilson (1998), involves the repeated simulation of the Data Generating Process (DGP) via re-sampling the surveyed data set. Put in another way, bootstrapping involves re-sampling the original data by replicating it several times via adjustment of the data generating process to generate new or pseudo or bogus data. The bootstrapping technique basically involves a Monte Carlo test the simplest form of bootstrap. The Monte Carlo approximation is applied to simulate the Data Generating Process (DGP) to generate valid estimator of the true unknown DGP (Gocht and Balcombe, 2006). Bootstrapping creates an avenue to test and confirm whether or not the data set from the observations are influenced by stochastic effects via the bias estimates and it has the ability to construct confidence interval for bias-corrected scores which would have been otherwise impossible be derived analytically (Gocht and Balcombe, 2006). The idea of bootstrapping is predicated on one of the major limitations of DEA estimatoras noted by Linh (2012) that its result lacks statistical property which leads to biased DEA estimates and hence spurious. To overcome this problem, Simar and Wilson (2000) argue that bootstrapping is currently the most feasible approach for establishing a consistent statistical property of a DEA estimator subjecting the DEA scores to further estimation to obtain a more robust and reliable DEA scores through bootstrapping. Linh (2012) based on his studies asserted that the DEA scores generated on the same data set with Stochastic Frontier Analysis (SPF), the DEA yield higher scores than the SPF. However, applying the smoothed bootstrapping technique as by Simar and Wilson (2000), the DEA scores reduce in magnitude to a closer range with the SPF scores and hence the difference between the original DEA and the bootstrapped DEA stands as the error term. In this study, the smoothed bootstrapping method developed by Simar and Wilson was used in which Linh (2012) argue that the efficiency scores are assumed to exhibit independent distribution and are generated by only adjusting the input vectors to create new DEA efficiency scores. Bootstrapping method is quick and simple to apply and generates reliable estimates whose correction bias is captured by the difference between the original estimates and the mean of the bootstrapped replicates using packages such as FEAR, BOJA, SAS and AMOS.

The efficiency of a unit point estimate (xk, yk) represented as $\theta_k = \{\theta/\theta_{xk} \in X\ (y_k)\}$ where X (y_k) represents set of input bundles. Suppose $\theta_k = 1$, unit k becomes ostensibly input efficient. For values of $\theta_k \leq 1$, varying level of input reduction on the unit k is feasible in order to achieve full efficiency as in the previous condition. Simar and Wilson (1998) defined y_k as the efficient input level commensurate to the level of output. Thus, y_k as $x^{\theta} = (x_k/y_k) = \theta_k x_k$. Where θ_k represents radial measure of distance between x_k and y_k and the corresponding frontier. θ_k is the variable of interest which is to be estimated and until estimated it remains unknown since, both X (y) and $\theta_k x_k$ are also unknown.

Procedures of data generating process (dgp): Gocht and Balcombe (2006) elucidated that in the DGP set up, P generates random sample $X = \{x_k y_k,\ k = 1, ..., n\}$ Applying non-parametric approach on the data X results to the scenario:

$$\hat{\theta}_k = \min\left\{ \begin{matrix} \theta \left| y_k \leq \sum_{i=1}^{n} y_i y_i \right| \theta_{xk} \geq \sum_{i=1}^{n} y_i x_i \left| \sum_{i=1}^{n} y_i = 1, y_i \geq 0 \right| \\ \theta \geq 0 | i = 1, ..., n \end{matrix} \right\} \tag{1}$$

Estimating the efficiency $\hat{\theta}_k = \min\{\theta | \theta_{xk} \in \hat{X}(y_k)|\}$ helps to obtain $\hat{X}$ and $\partial\hat{X}(y)$. Since in the DGP and is unknown, the bootstrap method helps to obtain DGP P as a meaningful estimator of the true unknown DGP obtained via the data $\hat{P}$. The efficiency estimates are viewed as new population and serves as a source from which new data set or pseudo data $X^* = \{x_i^* y_i^*,\ i = 1, ..., n\}$ are drawn. These pseudo data can predict the corresponding quantities $\hat{X}^*(y)$ and $\partial\hat{X}^*(y)$. Note these predictions are conditional on X and since $\hat{P}$ is known $\hat{X}^*(y)$ and $\partial\hat{X}^*(y)$ are also known. It is obvious that $\hat{P}$ may be difficult to compute analytically, hence the Monte Carlo approximation is applied to obtain the sampling distribution by predicting $\hat{P}$ to generate B pseudo samples x_b^*, where b = 1, ... B and pseudo estimates of the efficiency scores. The empirical distribution of pseudo estimates approximates for the unknown sampling distribution of the efficiency values.

Selection of bootstrap method and steps involved in the selected method: Gocht and Balcombe (2006) asserted that the naive bootstrap generates inconsistent estimates and that the homogenous smoothed bootstrap method introduced by Simar and Wilson (1998) is an easily implementable algorithm which generates, consistent bootstrap values from kernel density estimates and the very wide application of the homogenous smoothed bootstrap method in the field of agriculture are perhaps the justification for the choice and application of the homogenous smoothed bootstrap method in this study.

The steps involved in the homogenous smoothed bootstrap estimator are as follows:

- For any given DMU as k and input-output data as ($x_k y_k$). If k = 1, ..., n, compute $\hat{\theta}_k$ using linear programming to obtain the efficiency estimators. In this case, the specifications of the linear model are different estimators of the same unknown θ_k. Thus, $\hat{\theta}_k$ estimators represent random variables and ordinarily a specific realization of different random variables
- The smoothed bootstrap sample θ_1^*, ..., θ_n^* for i = 1, ..., n are generated by making β_1^* ,..., β_n^* a simple bootstrap sample derived by drawing with replacement. Thus, a random sample size can be obtained as follows:

$$\tilde{\theta}_i^* = \begin{cases} \beta_i^* + h\varepsilon_i^* & \text{if } \beta_i^* + \varepsilon_i^* \le 1 \\ 2 - \beta_i^* - h\varepsilon_i^* & \text{otherwise} \end{cases} \tag{2}$$

And the corrected bootstrap sample is obtained via:

$$\theta_1^* = \bar{\beta}^* + 1/\left(\frac{\sqrt{1+h^2}}{\hat{\partial}_{\hat{\theta}}^{\,2}}\right)\left(\tilde{\theta}_1^* - \bar{\beta}^*\right) \tag{3}$$

Where, $\bar{\beta}^* = 1/n\,\Sigma_{i=1}^n \beta_i^*, \hat{\delta}_{\hat{\theta}}^2$ denotes the sample variance of θ_1^*, ..., θ_n^*, h as the bandwidth factor and ε_i^* as random deviate. In accordance with (Simar and Wilson, 1998) on the computation of bandwidth factor and suggested the use of normal reference rule and set the bandwidth $h = 1.06\hat{\delta}_{\hat{\theta}}^2 n^{-1/5}$ as for a normally distributed data set $(\hat{\theta})$. Furthermore, they suggested the use of least square cross validation that relies on choice of bandwidth that minimizes an approximation to mean integrated square errors for non-normally distributed data set. The second method is applicable in DEA estimation, being a non-normally distributed data set, hence in this research, the least square cross validation approach was used.

Use the smoothed bootstrap sample sequence earlier to compute the new data $x_b^* = \{(x_{ib}^*, y_i) | i=1,...,n\}$ where:

$$x_{ib}^* = \left(\frac{\hat{\theta}_i}{\theta_{ib}^*}\right) x_i, \{i=1,...,n\}$$

Finally, compute the bootstrap efficiency estimates $\{\hat{\theta}_i^* | i=1,...,n\}$. This is done by using the new data x_b^* to solve the DEA model for each DMU. An example is illustrated for a single DMU, k = 1, the bootstrap estimates $\hat{\theta}_{kb}{}^*$ can be obtained by solving the model:

$$\hat{\theta}_{k,b}^* = \min\left\{ \theta > 0 \middle| y_k \le \Sigma_{i=1}^n y_i y_i \middle| \theta_{xk} \ge \Sigma_{i=1}^n y_i x_{i,b}^* \middle| \Sigma_{i=1}^n y_i = 1, y_i \ge 0, i=1,...,n \right\} \tag{4}$$

Steps 2-4 are iterated B times to provide for k = 1, ..., n a set of estimates $\{\hat{\theta}_{k,b}^*, b=1,...,B\}$. Simar and Wilson (1998) recommended a minimum of 2000 bootstrap iterations in line with that in the current study, B was also set at 2000. The bootstrap efficiency scores $\hat{\theta}_k^*$ and DEA efficiency scores $\hat{\theta}_k$ represents approximations to $\hat{\theta}_k$ and θ_k, respectively.

Estimation of bootstrap bias: Bias is defined as the difference between the original efficiency point estimates otherwise referred in this study as non-bias corrected efficiency estimates and the new bootstrap efficiency estimates otherwise referred as bias-corrected efficiency estimates in this study. Simar and Wilson (2000) denoted the bootstrap estimate as $\{\hat{\theta}_{k,b}^*, b=1,...,B\}$ biased. The bias estimate can be obtained from bootstrap procedure as follows:

$$\text{BIAS}\left(\hat{\theta}_k\right) = E\left(\hat{\theta}_k\right) - \theta$$

Empirically, the bootstrap bias for the original estimator $\hat{\theta}_k$ is thus:

$$\text{BIAS}_B\left(\hat{\theta}_k\right) = B^{-1}\left(\sum_{b=1}^{B} \hat{\theta}_{k,b}^*\right) - \hat{\theta}_k$$

The bias corrected estimator is realized via the original efficiency estimates less the bias component. Bias may sometimes be negative, particularly when Sheppard's distance function is sought for in the FEAR software but in this study the Farrell's convention was adopted and hence, the biases were positive.

Estimation of confidence interval: Simar and Wilson (1998) proposed 4 categories of confidence interval: Efron percentile interval, Hall percentile interval based on difference, Efron's bias corrected intervals and percentile intervals based on ratios. The Hall percentile interval based on differences was adopted in this research due to its simplicity. The confidence interval is normally build for the bias-corrected efficiency estimates or bootstrapped scores of every single DMU, k. If the distribution of $\left(\hat{\theta}^*(x,y) - \theta(x,y)\right)$ is known then possibility abounds for obtaining a_a, b_b such that:

$$P_r\left(-b_a \le \hat{\theta}_k(x_0, y_0) - \theta(x_0, y_0) \le -a_a\right) = 1 - a \tag{5}$$

Since, a_a and b_a are unknown terms, researchers use $\{\hat{\theta}_{k,b}^*, b=1,...,B\}$ to predict them as $\hat{a}_a$ and $\hat{b}_a$ thus, researchers get:

$$_r\left(-\hat{b}_a \le \hat{\theta}^*_{k,b}\left(x_0,y_0\right) \le -\hat{a}_a \left|\hat{P}\left(X_n\right)\right.\right)=1-a \qquad (6)$$

Predicting $\hat{a}_a$ and $\hat{b}_a$ implies sorting values as $\hat{\theta}^*_{k,b}(x_0,y_0)-\hat{\theta}_k(x_0,y_0), b=1,...,B$ in ascending order and deleting $[(a/2)\times100]^{\%}$ of rows at each end of the list and setting $-\hat{b}_a$ and $-\hat{a}_a$ to the extreme points of the array with $\hat{a}_a \le \hat{b}_a$. The 1-a percent confidence interval then becomes:

$$\hat{\theta}_k=\left(x_0,y_0\right)+\hat{a}_a \le \theta\left(x_0,y_0\right) \le \hat{\theta}_k\left(x_0,y_0\right)+\hat{b}_a \qquad (7)$$

This process is replicated n times to derive n confidence interval for any given DMU.

Factors influencing technical efficiency: In this study, the farmers/farm specific characteristics were regressed against bias-corrected technical efficiency to determine factors influencing the technical efficiency. Earlier, correlation test was conducted on the independent variables to aid the selection of relevant variables for inclusion in the tobit and OLS regression. The equation determining factors influencing the technical efficiency is presented:

$$\begin{aligned} TE_{bias-corrected} = \psi_0 + \psi_1 Z_1 + \psi_2 Z_2 + \psi_3 Z_3 + \\ \psi_4 Z_4 + \psi_5 Z_5 + \psi_6 Z_6 + \varepsilon_i \end{aligned} \qquad (8)$$

Where, Z_1, ..., Z_6 represents age of farmer, years of education, years of integration, extension visit, farmers' association and credit, respectively.

Data collection: Cross sectional data were collected from both goat-oil palm and cattle-oil palm farmers across the entire 10 districts (Batu Pahat, Johor Bahru, Kluang, Kota Tinggi, Kulaijaya, Ledang, Mersing, Muar, Pontian and Segamat) of Johor State, Malaysia. The nature of data were comprehensively production data for the year 2011 (January to December) and the data collection was between January and August, 2012. After correcting for outliers, 255 sample size or farms were used in the analyses herein. A FEAR 1.15 Software developed by Wilson (2010) hosted on a 32-bit R version 2.14.0 was used for the estimation. FEAR provides estimates under both Farrell's and Sheppard's distance function in the current study, all estimates were reported based on the Farrell's efficiency both conventions are a reciprocal of one another. This enable the bias estimates to assume positive values and efficiency scores to range between 0 and 1. All estimations are based on the assumption of input orientation.

RESULTS AND DISCUSSION

Outlier detection and summary statistics for inputs and output variables used: The box and whiskers plots in Fig. 1 and 2, plotted after the elimination of outliers did not show the presence of outliers in the data sets for both goat-oil palm and cattle-oil palm. Outliers were initially detected in some observations when the initial plots were constructed and after elimination, the plots here confirm. It is obvious that no observation lies beyond the whiskers region all observations lies either within the box or the whiskers region an indication that the data is free of extreme values. Outlier analysis is crucial step when estimating efficiency, particularly when dealing with estimation techniques that are sensitive to outliers or extreme values as in the case of the current research. Efficiency studies such as (Gocht and Balcombe, 2006) and numerous others have conducted the outlier test in line with such studies researchers also conducted the outlier test. The box and whiskers plots explains

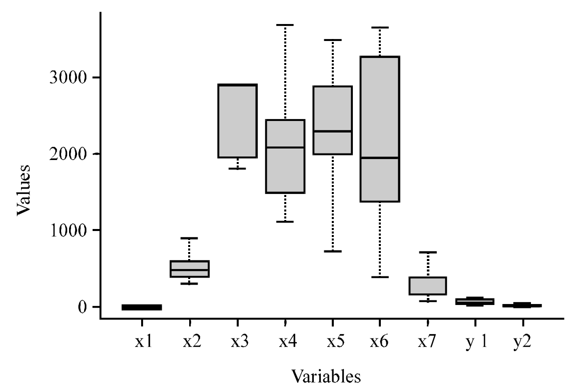

Fig.1: Box and whiskers plots for outlier detection and description of the statistical pattern of the data used for goat-oil palm integration

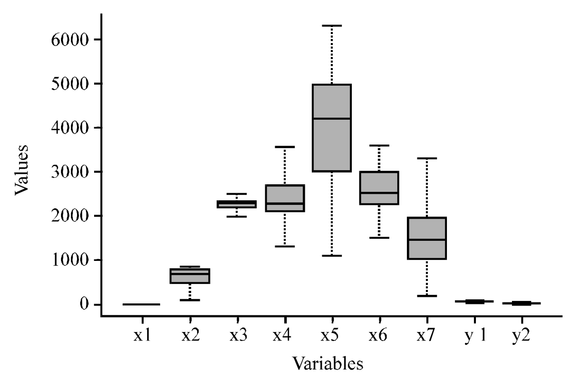

Fig. 2: Box and whiskers plots for outlier detection and description of the statistical pattern of the data used for cattle-oil palm integration

extensively other statistical behaviors of the data sets for instance, information about range, lower-quartile, middle-quartile (median), upper-quartile, inter-quartile range, skewness, kurtosis, normality of the data can all be deduced from the box and whiskers plots.

Table 1 and 2 describe 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 farm size, the cattle-oil palm plantations maintain relatively larger farm size with a mean of 4.05 ha over the goat-oil palm plantations with a mean of 3.64 ha. The relatively larger farm size of the cattle-oil palm plantations perhaps explains the higher farm maintenance costs with a mean of RM624.70 over goat-oil palm plantations with a mean of RM510.30. The same reasoning of large farm size may be adduced to capital (RM2414.00), hired labour (RM2658.00) in cattle-oil palm as against capital (RM2034.00) and hired labour (RM2135.00) in the goat-oil palm plantations. The farm size index and stocking rate of animals are important in explaining the variation in use of fertilizer, family labour and other costs. For instance, the fact that the cattle-oil palm plantations keep more (mean = 40) animals than the goat-oil palm plantations (mean = 27), 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 than 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 its 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/year in former than 66.81MT/year in the latter.

Result of homogeneous smoothed bootstrap for optimizing technical efficiency: Results were estimated and presented based on simulation technique generated by iterating or replicating the original data 2000 times. The result presents among others non-bias-corrected technical efficiency, bias-corrected technical efficiency, bias estimate and the lower and upper bounds confidence interval for the bias-corrected technical efficiency. While result in Table 3 reveals that the non-bias-corrected technical efficiency for goat-oil palm integration range between 0.623 and 1.000 with a mean score of 0.953, implying 95.3% efficiency level, its bias-corrected technical efficiency range between 0.598 and 0.945 with a mean score of 0.888, indicating 88.8% efficiency level. The estimated bias-corrected technical efficiency of 0.888 infers that on the average the goat-oil palm plantations could potentially reduce the utilization of input bundles by 11.2% and yet produce the same level of FFB and livestock output if the technology and management principles of the best practiced farms are imbibed by all farms. Similarly, the cattle-oil palm integration report a mean bias-corrected TE of 0.891. Examining the minimum scores, the mean scores and the number of plantations

Table 1: Descriptive statistics of variables for the efficiency analyses in goat-oil palm integration

Variables	Definition	Minimum	Maximum	Mean	SD
X1	Land (ha)	1.20	6.00	3.64	1.31
X2	Farm maintenance (RM/year) (maintenance of roads, paths and bridges and maintenance of farm building)	290.00	900.00	510.30	168.21
X3	Fertilizer (kg)	1800.00	2900.00	2480.00	480.06
X4	Capital (RM/year) (land tax, fuel cost for machines, maintenance of machines, tools and equipment, depreciation, establishment cost)	1106.00	3700.00	2034.00	649.05
X5	Family labour (Man-hour/year)	720.00	3500.00	2412.00	672.30
X6	Hired labour (RM) (major hired labour operations, harvesting and weeding (land clearing))	390.00	3660.00	2135.00	987.09
X7	Other costs (RM) (salt, brown sugar, medicine, vaccine and supplements)	75.81	716.00	318.11	176.47
Y1	Fresh fruit bunches yield (MT/year)	10.00	116.00	66.81	32.17
Y2	Livestock (No. of stock)	2.00	63.00	27.00	6.71

Table 2: Descriptive statistics of variables for the efficiency analyses in cattle-oil palm integration

Variables	Definition	Minimum	Maximum	Mean	SD
X1	Land (ha)	2.50	7.00	4.05	0.410
X2	Farm maintenance (RM/year) (maintenance of roads, paths and bridges and maintenance of farm building)	120.00	850.00	624.70	172.140
X3	Fertilizer (kg)	2000.00	2500.00	2293.00	139.345
X4	Capital (RM/year) (land tax, fuel cost for machines, maintenance of machines, tools and equipment, depreciation, establishment cost)	1309.00	3563.00	2414.00	449.200
X5	Family labour (Man-hour/year)	1080.00	6300.00	3954.00	1005.860
X6	Hired labour (RM) (major hired labour operations, harvesting and weeding (land clearing))	1500.00	3660.00	2658.00	560.060
X7	Other costs (RM) (salt, brown sugar, medicine, vaccine and supplements)	210.00	3312.00	1519.00	631.380
Y1	Fresh fruit bunches yield (MT/year)	50.00	120.00	88.58	18.670
Y2	Livestock (No. of stock)	10.00	80.00	40.00	15.170

Table 3: Technical efficiency, bias estimate and confidence interval for goat-oil palm and cattle-oil palm integration based on DEA-bootstrap estimator under VRS assumption

Efficiency range	Non-bias corrected $TE_{VRS\text{-}DEA\text{-}boot\text{-}estimator}$	Bias-corrected $TE_{VRS\text{-}DEA\text{-}boot\text{-}estimator}$	Bias estimate	Confidence interval Lower bound	Upper bound
Goat-oil palm					
<0.50	0	0			
0.51-0.60	0	1(1.54)			
0.61-0.70	5 (7.69)	4 (6.15)			
0.71-0.80	3 (4.62)	3 (4.62)			
0.81-0.90	2 (3.08)	6 (9.23)			
0.91-0.99	5 (7.69)	51 (78.46)			
1.000	50 (76.92)	0			
Summary					
Min	0.623	0.598	0.025	0.574	0.621
Max	1.000	0.945	0.081	0.875	0.998
Mean	0.953	0.888	0.065	0.764	0.950
SD	0.104	0.088	0.018	0.064	0.103
Cattle-oil palm					
<0.50	8 (4.21)	9 (4.74)			
0.51-0.60	12 (6.32)	21 (11.05)			
0.61-0.70	21(11.05)	21 (11.05)			
0.71-0.80	17 (8.95)	22 (11.58)			
0.81-0.90	20 (10.53)	103 (54.21)			
0.91-0.99	13 (6.84)	14 (7.37)			
1.000	99 (52.11)	0			
Summary					
Min	0.430	0.416	0.013	0.388	0.429
Max	1.000	0.971	0.076	0.915	0.999
Mean	0.938	0.891	0.047	0.776	0.937
SD	0.114	0.102	0.020	0.089	0.114

lying closer to the frontier, it could be seen that some degree of dispersion exist and by extension it implies 10.9% inefficiency level. The non-bias-corrected technical efficiency less the bias-corrected technical efficiency yields the bias estimate. Except for the simulation effect in it, the non-bias-corrected TE was estimated based on traditional DEA approach with the noise component not embedded, the bias-corrected TE obviously account for noise which corresponds to the bias. Thus, the justification behind lower values of bias-corrected TE compared to the non-bias-corrected TE. The bias account for factors beyond farmers' control, such as flood, diseases, climate, policy shocks and other natural hazards, it also adjust for best practice farms not included in the samples. The mean bias estimate of 0.065 and 0.047 for goat and cattle integration, respectively indicates that more noise exist in the former and further indicates the latter as a better system. It was observed also that these farms under both systems operate under similar exogenous factors, similar climate, policy shocks from government and diseases. Except of course, the goats were found to suffer when exposed to torrential rainfall, particularly if no befitting housing is constructed and this lead to reduced performance and sometimes death of the goats. Furthermore, more goats were lost compared to cattle in the 2011 floods that engulfed the state. The foregoing discoveries on rainfall and flood are the inference that accounts for the higher noise or bias in the goat-oil palm relative to the cattle-oil palm integration in the area. Similarly, estimation under CRS and NIRTS as shown in Table 4 and 5 did not show much difference in bias-corrected TE across the 2 systems but the estimations are lower compared to those reported under the VRS assumption. This is of course expected since theory repeatedly holds that since the data are loosely enveloped under the VRS model, it generates higher scores than the CRS model with a tighter envelop. Again, the cattle system.

Evidence in Table 6 exist to show varying degree of scale inefficiency in production across the systems of integration studied, goat-oil palm and cattle-oil palm with mean SE scores of 0.708 and 0.734, respectively is an indication that the plantations are scale inefficient. While the goat-oil palm plantations are 29.2% away from the scale frontier, the cattle-oil palm is 26.6% scale inefficient, by implication, the cattle-oil palm is better a scale efficient system than the goat-oil palm. Also that the PTE or VRS TE of 0.888 and 0.891 for goat and cattle systems, respectively are higher than their respective SE scores. This suggest that the principal source of overall technical efficiency appears to be more of scale related rather than technical issues such as poor management. This further implies that gains in technical efficiency are feasible via increased scale of operation (farm size). This perhaps is expected owing to the fact that the farmers are small holders by scheme and operates just a few hectares

Table 4: Technical efficiency, bias estimate and confidence interval for goat-oil palm and cattle-oil palm integration based on DEA-bootstrap estimator under CRS assumption

Efficiency range	Non-bias corrected $TE_{CRS\text{-}DEA\text{-}boot\text{-}estimator}$	Bias-corrected $TE_{CRS\text{-}DEA\text{-}boot\text{-}estimator}$	Bias estimate	Confidence interval Lower bound	Upper bound
Goat-oil palm					
<0.50	11 (16.92)	17 (26.15)			
0.51-0.60	9 (13.85)	9 (13.85)			
0.61-0.70	5 (7.69)	2 (3.08)			
0.71-0.80	3 (4.62)	23 (35.38)			
0.81-0.90	8 (12.31)	14 (21.54)			
0.91-0.99	2 (3.08)	0			
1.000	27 (41.54)	0			
Summary					
Min.	0.163	0.139	0.024	0.121	0.161
Max.	1.000	0.867	0.235	0.745	0.990
Mean	0.765	0.635	0.130	0.533	0.754
SD	0.263	0.207	0.063	0.171	0.260
Cattle-oil palm					
<0.50	49 (25.75)	70 (36.84)			
0.51-0.60	19 (10.00)	15 (7.89)			
0.61-0.70	17 (8.95)	18 (9.47)			
0.71-0.80	16 (8.42)	66 (34.74)			
0.81-0.90	13 (6.84)	21 (11.05)			
0.91-0.99	9 (4.74)	0			
1.000	67 (35.26)	0			
Summary					
Min.	0.180	0.156	0.024	0.134	0.179
Max.	1.000	0.882	0.213	0.810	0.994
Mean	0.775	0.661	0.115	0.567	0.767
SD	0.230	0.185	0.052	0.156	0.228

Generated lower bias (CRS = 0.115 and NIRTS = 0.116) than the goat system (CRS = 0.130 and NIRTS = 0.131) and still inferring that the cattle with less bias has better shield on factors beyond farmers control than the goat system

Table 5: Technical efficiency, bias estimate and confidence interval for goat-oil palm and cattle-oil palm integration based on DEA-bootstrap estimator under NIRTS assumption

Efficiency range	Non-bias corrected $TE_{NIRTS\text{-}DEA\text{-}boot\text{-}estimator}$	Bias-corrected $TE_{NIRTS\text{-}DEA\text{-}boot\text{-}estimator}$	Bias estimate	Confidence interval Lower bound	Upper bound
Goat-oil palm					
<0.50	11 (16.92)	17 (26.15)			
0.51-0.60	9 (13.85)	9 (13.85)			
0.61-0.70	5 (7.69)	2 (3.08)			
0.71-0.80	3 (4.62)	23 (35.38)			
0.81-0.90	8 (12.31)	14 (21.54)			
0.91-0.99	2 (3.08)	0			
1.000	27 (41.54)	0			
Summary					
Min.	0.163	0.139	0.024	0.121	0.161
Max.	1.000	0.868	0.231	0.743	0.991
Mean	0.765	0.633	0.131	0.526	0.755
SD	0.263	0.206	0.064	0.167	0.260
Cattle-oil palm					
<0.50	49 (25.75)	68 (35.79)			
0.51-0.60	19 (10.00)	19 (10.00)			
0.61-0.70	17 (8.95)	16 (8.42)			
0.71-0.80	16 (8.42)	67 (35.26)			
0.81-0.90	13 (6.84)	20 (10.53)			
0.91-0.99	9 (4.74)	0			
1.000	67 (35.26)	0			
Summary					
Min.	0.180	0.156	0.024	0.134	0.178
Max.	1.000	0.874	0.213	0.797	0.993
Mean	0.776	0.660	0.116	0.562	0.768
SD	0.230	0.185	0.053	0.152	0.228

and the assumption of zero frontiers surrounding the DEA-bootstrap estimator makes no surprise out of this finding. Having justified that all the farms operates under sub-optimal conditions owing to size of production under both integration systems, a further analysis of NIRTS was conducted and compared with the VRS model to ascertain the nature of returns to scale of the farms. Accordingly, unequal magnitudes emanated following the comparison and infer that all the farms, under both integration systems operates under Increasing Returns To Scale (IRTS) of production.

Tobit and OLS results for determining factors influencing technical efficiency: Conventionally, determinants of technical efficiency are determined using the tobit regression. Abatania *et al.* (2012) argued that when technical efficiency is corrected for bias (bias-corrected TE) as was the case in this research, tobit is no longer appropriate for examining the determinants of the bias-corrected TE, instead, an Ordinary Least Square estimator (OLS) was suggested as the suitable approach.

Table 6: Scale efficiency and nature of returns to scale in goat-oil palm and cattle-oil palm integration systems

Efficiency range	SE = (CRS/VRS)	RTS = (CRS/NIRTS)
Goat-oil palm		
<0.50	10 (15.38)	0
0.51-0.60	8 (12.31)	0
0.61-0.70	5 (7.69)	0
0.71-0.80	10 (15.38)	0
0.81-0.90	25 (38.46)	0
0.91-0.99	7 (10.76)	18 (27.69)
1.000	0	47 (72.31)
		65 (100.00)-IRTS (sub-optimal scale)
Summary		
Min.	0.160	0.993
Max.	0.942	1.000
Mean	0.708	1.000
SD	0.209	0.005
Cattle-oil palm		
<0.50	24 (12.63)	0
0.51-0.60	10 (5.26)	0
0.61-0.70	27 (14.21)	0
0.71-0.80	23 (12.11)	0
0.81-0.90	51 (26.84)	0
0.91-0.99	55 (28.95)	102 (53.68)
1.000	0	88 (46.32)
		190 (100.00)-IRTS (sub-optimal scale)
Summary		
Min.	0.237	0.957
Max.	0.928	1.000
Mean	0.734	1.000
SD	0.170	0.005

In the present study, both the tobit and OLS were ran to satisfy both school of thoughts. Table 7 presents, the results of the tobit regression for goat-oil palm integration and cattle-oil palm integration, respectively. In each case, the bias-corrected TE score was ran as dependent variable against farmers' age, years of farmers' education, years of integration, extension visits, farmers association and capital as explanatory variables. The results have shown consistency in terms of signs of coefficients and level of significance across both integration systems. However, the t-values are larger and the magnitude of the coefficients are insignificantly smaller in the goat-oil palm integration relative to cattle-oil palm integration and these may not be unconnected with larger sample size of the former relative to the latter. Results shows as expected all the six explanatory variables with positive coefficients and except for extension visit which shows moderately significant (5% level) relationship, all the remaining 5 variables show highly significant (1% level) relationship with the explanatory variable. In other words, all the 6 variables (age, education, integration experience, extension visit, farmers association and capital) positively influence technical efficiency in the goat-oil palm integration and cattle-oil palm integration, respectively. This finding is consistent with theory studies, such as Abatania *et al.* (2012), Mugera and Featherstone (2008) and Dhungana *et al.* (2004) and several others have shown a positive and significant relationship between TE in agriculture and farmers' age. This positive relationship between age and TE implies that older farmers are more efficient than younger farmers in the 2 systems of integration and this is because older farmers garner more production experience than younger farmers and hence, impacts positively on the TE. The positive relationship obtained between TE and farmers' education could be explained on the premise that highly educated farmers are more efficient than farmers with low level of education or entirely uneducated farmers. The justification for this is that more educated farmers are anticipated to be more

Table 7: Tobit analyses of factors influencing technical efficiency in goat-oil palm and cattle-oil palm integration

	Goat-oil palm			Cattle-oil palm		
Bias-corrected TE score	Coefficient (SE)	t-value (p-value)	Confidence interval (lower-upper)	Coefficient (SE)	t-value (p-value)	Confidence interval (lower-upper)
Age of farmer (years)	0.03051 (0.00130)	23.47 (0.000)***	0.02791-0.03310	0.03057 (0.00076)	40.22 (0.000)***	0.02907-0.03208
Education (years)	0.02346 (0.00350)	6.69 (0.000)***	0.16444-0.03047	0.02355 (0.00204)	11.52 (0.000)***	0.01952-0.02758
Integration (years)	0.01066 (0.00098)	10.87 (0.000)***	0.00869-0.01263	0.01057 (0.00060)	17.62 (0.000)***	0.00940-0.11750
Extension visit	0.00633 (0.00266)	2.38 (0.021)**	0.00100-0.11654	0.00623 (0.00159)	3.92 (0.000)***	0.00309-0.00937
Farmer's association	0.44536 (0.02569)	17.34 (0.000)***	0.39396-0.49677	0.44494 (0.01539)	28.91 (0.000)***	0.41459-0.47530
Credit	0.01478 (0.00161)	9.18 (0.000)***	0.11551-0.01801	0.01466 (0.00098)	14.95 (0.000)***	0.01273-0.01661
Constant	0.49582 (0.02421)	20.48 (0.000)***	0.44738-0.54425	0.49733 (0.01427)	34.85 (0.000)***	0.46916-0.52549
Summary statistics	N = 65			N = 190		
Prob>χ^2	0.0000			0.0000		
Pseudo R^2	5.5431			5.6613		
Log likelihood	180.38194			533.24015		

Table 8: OLS analyses of factors influencing technical efficiency in goat-oil palm and cattle-oil palm integration

Bias-corrected TE score	Goat-oil palm Coefficient (SE)	t-value (p-value)	Confidence interval (lower-upper)	Cattle-oil palm Coefficient (SE)	t-value (p-value)	Confidence interval (lower-upper)
Age of farmer (years)	0.03536 (0.00145)	24.40 (0.000)***	0.03246-0.03826	0.03523 (0.00079)	44.37 (0.000)***	0.03366-0.03680
Years of education	0.03063 (0.00452)	6.78 (0.000)***	0.02159-0.03967	0.02997 (0.00247)	12.13 (0.000)***	0.02509-0.03485
Years of integration	0.01036 (0.00130)	7.99 (0.000)***	0.00777-0.01296	0.01020 (0.00073)	13.97 (0.000)***	0.00875-0.01164
Extension visit	0.00032 (0.00349)	0.09 (0.928)NS	0.00667-0.00731	0.00002 (0.00193)	0.01 (0.993)NS	0.00379-0.00383
Farmer's association	0.38884 (0.03384)	11.49 (0.000)***	0.32112-0.45657	0.38460 (0.01866)	20.61 (0.000)***	0.34779-0.42142
Credit	0.00940 (0.00202)	4.66 (0.000)***	0.00536-0.01343	0.00909 (0.00113)	8.04 (0.000)***	0.00687-0.01132
Constant	0.59487 (0.02625)	22.66 (0.000)***	0.54231-0.64741	0.59319 (0.01439)	41.22 (0.000)***	0.56479-0.62159
Summary statistics	N = 65			N = 190		
Prob>F	0.0000			0.0000		
R^2	0.9993			0.9993		
Adjusted R^2	0.9992			0.9993		

skillful, more result-oriented, more rational and responsive to farm management decisions. Similarly, positive and significant relationship between education and agricultural TE were obtained by numerous studies; notably: Linh (2012), Gul *et al.* (2009), Balcombe *et al.* (2008), Mugera and Featherstone (2008), Dhungana *et al.* (2004) and Paul *et al.* (2004) and many others. Years of integration experience have also shown consistent positive and highly significant association with the TE across the integration systems. Years of integration experience is indeed vital in explaining TE as farmers with more integration years were found to be more efficient than farmers with low years of integration experience.

Researches, such as Padilla-Fernandez and Nuthall (2009), Olson and Vu (2009), Gul *et al.* (2009) and Mugera and Featherstone (2008) have also found similar statistical relationship between farming experience and TE. Farmers who enjoy many contacts with extension agents became more efficient than those with less or no contact with extension agents thus, a positive effect on TE. Extension education creates an avenue for farmers to be acquainted with latest production technique to enhance productivity and efficiency. Balcombe *et al.* (2008) and many other studies established similar positive effect between extension and efficiency in Bangladesh rice farming. Looking at the role capital plays in agriculture, its positive effect on TE is indeed not surprising. Farmers with better capital for sourcing inputs become more efficient than those who were not capital worthy. Vu (2012) Monchuk *et al.* (2010), Padilla and Nuthall (2009), Balcombe *et al.* (2008) and Mugera and Featherstone (2008) also found similar positive results in the various studies. Table 8 presents the OLS results for the systems based on the emerging scholarly evidence in the line of Abatania *et al.* (2012) proposing OLS as suitable for determining factors influencing TE under bias- corrected scenario. The OLS results reveal little variations in the parameters estimated and except for extension visit which shows insignificant relationship with technical efficiency across both systems, all other variables show consistently positive and significant relationship with technical efficiency as in the tobit results. The significance of the F statistics and the very high R^2 values in both systems, suggesting that the variables included have explained 99.93% of the variations in technical efficiency.

CONCLUSION

Comparatively, the cattle-oil palm integration show evidence of higher efficiency and accommodates lower bias than the goat-oil palm integration. The 2 systems appear to have similarities in some bias factors like climate, policy shocks and diseases, perhaps their major variability was in torrential rainfall and flood components of the bias which devastated the goats more than it did to the cattle in 2011 and hence the rationale for the larger bias in the goat relative to the cattle. Farm decisions aimed at mitigating the effect of noise in the system is an avenue to achieving higher efficiency for instance proper housing for the goats will help subvert the effect of rainfall on the goats and hence, prevent them from undergoing reduced performance and possible death. Small farm size nature of the plantations rather than poor management appear to explain the inefficiencies in the system, adopting a decision to increase farm size shall aid reduce the inefficiency levels, produce more output and at a much lower cost of production.

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