

Robust Efficiency and Output Elasticity of Broiler Production in Peninsular Malaysia

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ABSTRACT

This study investigates issues on efficiency and elasticity of broiler production in Peninsular Malaysia. Data from 296 broiler farms were subjected to SFA, DEA and bootstrap methods for technical efficiency; Translog and Tobit regression analyses to estimate elasticity of production and determinants of efficiency respectively in broiler production. We found that farmers produce mean efficiency of 94, 95 and 97% with robust for small, medium and large scale farms respectively. Apart from inefficiency, we also found evidence that minimal bias/noise exists in broiler production. Relative to output elasticity, we observed an inelastic relationship in feeds but an elastic relationship in DOC, medications and utilities. Most of the socio-economic attributes (experience, age, education, business status and number of farms) show highly significant statistical relationship with efficiency and with appropriate signs. To ensure production at higher marginal returns and lower marginal costs, farms operating under increasing returns to scale should scale-up production while those producing at decreasing returns to scale need to scale-down production. The study also advocates to farmers to embrace adequate training/better education, contract farming and ownership of fewer number of farms in order to enhance efficiency, productivity and sustainability of the broiler industry.

Keywords: Bias, Bootstrap, Technical, Tobit, Translog.

INTRODUCTION

To achieve global food security for over 7 billion inhabitants of the earth, analyses and assessments of food security situation is imperative. FAO (1996) states “food security exists when all people, at all times have access to sufficient, safe and nutritious food to meet their dietary needs and food preferences for an active and healthy life”.

To measure food security, the production status of both crop and livestock components are often appraised and evaluated vis-à-vis its population. The livestock component relative to the crop component supply excellent key micro-nutrients (such as iron, zinc and vitamin A) and numerous others, these nutrients are better absorbed from the animal source than the plant source (FAO, 2010). The study of the

broiler production, a subset of poultry (animal-source) is indeed necessary being one of the cheap sources of animal protein to achieve the goal of food security.

Malaysia with a current population of 30.14 million (DSM, 2014) has attained the food self-sufficiency level in broiler production since 2004. The broiler industry contributes 11.5% of the nation's GDP as at 2010, employing thousands and generating substantial revenue yearly. In line with the food security guidelines, persistent appraisal of agricultural production components is indeed vital. This is further necessitated by the rising cost of production. The high cost of broiler production (feed cost) in developing economies call for concern. Ravindran (2013) stated that feed cost in broiler production accounts for about 70% and 22% of day old chicks and total variable cost respectively,

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while labor, vitamin and equipment jointly attracts only 9%. Similarly in Malaysia, Ariffin *et al.* (2014) stated that the poultry industry in Malaysia is confronted with high cost of feeds as chief regulator of costs of production; which accounts for 70% of production costs. The ability to meet the protein and amino acid requirements of the birds constitutes the greatest cost in the broiler feeds (Corzo *et al.*, 2004 and Darsi *et al.*, 2012). However, the use of phytase nutrient equivalency values in feed formulation for broiler helps improve feed costs and nutrients availability (Zaghari, 2009). Given the above information on high costs of production, this study is anchored on the foregoing. The study therefore unraveled the current resource-use efficiency status via robust approach, estimating output elasticity and identifying important socio-economic attributes enhancing efficiency of broiler production. This study provides necessary information for future studies on sustainability of broiler production in Malaysia. The article is therefore structured in the following sections: introduction, methodology, results and discussion and finally conclusion.

MATERIAL AND METHODS

Study Area

Malaysia as a whole is divided into two segments; West and East Malaysia. The West (Peninsular) part of Malaysia consists of eleven (11) out of the thirteen (13) States. The study was conducted in eight (8) (Melaka, Negeri Sembilan, Perak, Johor, Pinang, Kelantan, Selangor and Kedah states) out of the eleven (11) states in the peninsular. The peninsular shares borders with Singapore, Thailand, Indonesia, Borneo Island and South China Sea. It has a population of 23.5 million (80% of total population) in 2012 and constitutes 80% also of the Malaysian economy. The Peninsular is categorized into 4 regions namely; Northern, Southern, Central and East-Coast regions.

Sampling Method and Nature of Data

A stratified sampling technique was used for data collection with scale of production (small, medium and large) as strata. We adopted the DOC classification from the Department of Veterinary Services (DVS) Malaysia (2012). Based on the criteria, farms with DOC below 30,000 are classified as small farms; those with DOC between 30,001 and 120,000 are classified as medium farms while those with above 120,000 DOC are grouped as large farms (DVS, 2012). A total of six inputs and one output are used as variables for estimating efficiency. The variables include Y = Output (Kg of broiler), X_1 = DOC (Number of day old chicks), X_2 = Feeds (Kg), X_3 = Labor (Man-hours), X_4 = Medications (RM), and X_5 = Utilities (RM). However, in estimating the Translog production frontier, the unit of the output variable is transformed from kilogram to number of birds and logarithms of all the variables are calculated for the analysis. Similarly, the following variables are used for the Tobit analysis; (Y)= $TE_{bias-corrected}$, Ψ_1 = System of broiler production, Ψ_2 = Experience, Ψ_3 = Farmers' age, Ψ_4 = Farmers' education, Ψ_5 = Business status, Ψ_6 = Land status, and Ψ_7 = Number of broiler farmers. We used a combination of FEAR 1.15, FRONTIER 4.1 and STATA 12 softwares for the data analysis.

Data Analysis

DEA-Bootstrapping

The limitations of the DEA methodology, particularly its inability to address inference and its ability to handle only point estimates led to the concept of bootstrapping the DEA to overcome the limitations. Simar and Wilson (2000a) introduced a homogenous smoothed bootstrap methodology; an algorithm that yields consistent estimates of bootstrap values $\hat{\theta}_b^*$ based on the kernel density estimate of Simar and Wilson (1998) and Simar and Wilson (2000b). The

methodology provides also the bias and confidence interval as a means of satisfying the statistical inference and providing internal estimates hitherto not generated by the conventional DEA methodology. The step-wise procedure for the smoothed bootstrap algorithm can be executed as shown below:

Use the linear program below to compute $\hat{\theta}_k$ for each $(x_k, y_k) k = 1, \dots, n$

$$\hat{\theta}(x_o, y_o) = \min \left\{ \begin{aligned} &\theta > 0 | y_k \\ &\leq \sum_{i=1}^n \gamma_i y_i, \theta x_o \\ &\geq \sum_{i=1}^n \gamma_i x_i, \sum_{i=1}^n \lambda_i = 1, \gamma_i \\ &\geq 0, i = 1, \dots, n \end{aligned} \right\} \quad (1)$$

Then, with the aid of the smooth bootstrap, generate a random sample of size n from $\hat{\theta}_i, i = 1, \dots, n$ providing $\hat{\theta}_{1b}^*, \dots, n\hat{\theta}_{nb}^*$.

Next, solve the following equation:

$$\hat{\theta}^*(x_o, y_o) = \min \left\{ \begin{aligned} &\theta > 0 | y_k \\ &\leq \sum_{i=1}^n \gamma_i y_i, \theta x_k \\ &\geq \sum_{i=1}^n \gamma_i x_i^* k, b; \sum_{i=1}^n \lambda_i \\ &= 1, \gamma_i \geq 0, i \\ &= 1, \dots, n \end{aligned} \right\} \quad (2)$$

Where $x_{k,b}^* = \left(\frac{\hat{\theta}}{\theta_i^*} \right) x_i, i = 1, \dots, n$ and θ_i^* is the bias-corrected value and it is corrected with the following equation:

$$\theta^* = \bar{\beta}^* + \frac{1}{\left(\sqrt{1+h^2} / \hat{\sigma}_{\hat{\theta}}^2 \right) (\bar{\theta}_i^* - \bar{\beta}^*)} \quad \text{with } \bar{\beta}^* = 1/n \sum_{i=1}^n \beta_i^* \quad (3)$$

If $\beta_1^*, \dots, \beta_n^*$ denotes simple bootstrap sample from $\hat{\theta}_1, \dots, \hat{\theta}_n$ obtained by drawing with replacement from $\hat{\theta}_1, \dots, \hat{\theta}_n$ and a random generator below:

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

Where h is denoted as the bandwidth factor and ε_i^* denotes random deviation obtained from the normal standard.

Stochastic Frontier Analysis

This study also employs the famous Stochastic Frontier Analysis (SFA) proposed by Aigner *et al.* (1977) and Meeusen and Van den Broeck (1977). By its specification, the output variability in SFA is decomposed into noise effect and inefficiency effect; both a part of the composed error term. The SFA model for a cross sectional data based on Aigner *et al.* (1977) is expressed as:

$$Y_i = f(X_i; \beta) \cdot \exp(\varepsilon_i) \quad (5) \quad \square \square$$

$$= \underbrace{f(X_i; \beta)}_{\text{Deterministic Component}} \cdot \underbrace{\exp(V_i)}_{\text{Noise Effect}} \cdot \underbrace{\exp(-U_i)}_{\text{Inefficiency Effect}}$$

Where Y_i denotes output produced by observation i and $f(X_i; \beta)$ represents a desirable function (such as Cobb-Douglass or transcendental logarithmic) of the row vector of input (X_i) and a vector of unknown (β). The error term (ε_i) aggregates two independent components V_i and U_i with a relationship $\varepsilon_i = (V_i - U_i)$. The V_i denotes a random component (such as measurement errors, extreme weather etc) beyond managerial control, while the U_i is a non-negative component related to farm specific factors inhibiting the i^{th} farm from attaining maximum efficiency.



To estimate the parameters in Equation (1), distributional assumption about the two components of error term is necessary. The V_i are assumed to be independently, identically and normally distributed and have a zero mean and constant variance, $\sigma_v^2, [v_i \sim N(0, \sigma_v^2)]$. But according to literature, U_i assume various specifications and different distributions. In this study, we adopt the Battese and Coelli (1995) model which assume the distribution of the U_i as truncated (at zero) of the normal distribution with mean, μ_i and variance, $\sigma_u^2, [u_i \sim N(\mu_i, \sigma_u^2)]$. To estimate a production frontier, it is assumed that the boundary of production function is defined by the “best practice” farm. Thus, indicates the maximum potential output owing to a given bundle of inputs (X_i) expressed as:

$$Y_i^* = f(X_i; \beta) \cdot \exp(V_i) \quad (6)$$

Model Specification for Transcendental Logarithmic Frontier Production Function

This study assumes a transcendental logarithmic frontier production function with assumption of truncated normal distribution as the appropriate model for this analysis. The famous Cobb-Douglass model is common in frontier studies but, it imposes restriction on return to scale to assume the same value across farms and assume a constant elasticity of substitution as 1 (Coelli, 1995). Coelli (1995) stated that the transcendental logarithmic production frontier is less restrictive and allows the interaction of square and cross multiples to aid in improving the fitness of the model. The transcendental logarithmic model is presented as:

$$\begin{aligned} \ln Y_i = & \beta_0 + \sum_{j=1}^5 \beta_j \ln X_{ji} \\ & + 0.5 \sum_{j=1}^5 \sum_{k=1}^5 \beta_{jk} \ln X_{ji} \ln X_{ki} \\ & + (V_i - U_i) \quad (7) \end{aligned}$$

Where, $i=$ Represents the i^{th} broiler farmer, for $i= 1, 2, \dots, 141/123/32$ for the small, medium and large farms respectively. X_{ij} denotes level of input j used by i^{th} broiler farmer. $\beta_{jk} = \beta_{kj}$ assume symmetry due to the cross effects and the number 5 indicates the total number of input variables captured in the model.

Elasticity of Production

Elasticity of output relative to the various inputs is a function of level of input-use expressed as:

$$\frac{\partial \ln E(Y_i)}{\partial \ln X_{ji}} = \{ \beta_j + \beta_{jj} \ln X_{ji} + \sum_{k \neq j} \beta_{jk} \ln X_{ki} \} \quad (8)$$

Note, unlike in the Cobb-Douglass model, except upon normalizing the output and input variables, the first order coefficients are not interpreted as elasticity of output in the translog model (Coelli, 1995). To estimate the output elasticity for our translog model, Equation (8) above has been extended to the following partial derivatives to evaluate output elasticity with respect to DOC, feeds, labor, medications and utilities respectively.

$$\begin{aligned} \frac{\partial \ln Y}{\partial \ln x_1} = & \beta_1 + \beta_6 \ln x_1 + \beta_{11} \ln x_2 + \beta_{12} \ln x_3 \\ & + \beta_{13} \ln x_4 + \beta_{14} \ln x_5 \quad (9) \end{aligned}$$

$$\begin{aligned} \frac{\partial \ln Y}{\partial \ln x_2} = & \beta_2 + \beta_7 \ln x_2 + \beta_{11} \ln x_1 + \beta_{15} \ln x_3 \\ & + \beta_{16} \ln x_4 + \beta_{17} \ln x_5 \quad (10) \end{aligned}$$

$$\begin{aligned} \frac{\partial \ln Y}{\partial \ln x_3} = & \beta_3 + \beta_8 \ln x_3 + \beta_{12} \ln x_1 + \beta_{15} \ln x_2 \\ & + \beta_{18} \ln x_4 + \beta_{19} \ln x_5 \quad (11) \end{aligned}$$

$$\begin{aligned} \frac{\partial \ln Y}{\partial \ln x_4} = & \beta_4 + \beta_9 \ln x_4 + \beta_{13} \ln x_1 + \beta_{16} \ln x_2 \\ & + \beta_{18} \ln x_3 + \beta_{20} \ln x_5 \quad (12) \end{aligned}$$

$$\frac{\partial \ln Y}{\partial \ln x_5} = \beta_5 + \beta_{10} \ln x_5 + \beta_{14} \ln x_1 + \beta_{17} \ln x_2 + \beta_{19} \ln x_3 + \beta_{20} \ln x_4 \quad (13)$$

Tobit Regression

Seven socio-economic variables are used as independent variables in addition to the bias-corrected technical efficiency as dependent variable for the Tobit regression to explain important factors affecting efficiency of broiler production. The equation is presented as follows:

$$TE_{bias-corrected} = \Psi_0 + \Psi_1 Z_1 + \Psi_2 Z_2 + \Psi_3 Z_3 + \Psi_4 Z_4 + \Psi_5 Z_5 + \Psi_6 Z_6 + \Psi_7 Z_7 + \varepsilon_i \quad (14)$$

Where Z_1, \dots, Z_7 represents system of broiler production, experience, farmers' age, farmers' education, their business status, land status and number of broiler farms owned by farmers. The symbol Ψ_0 denotes intercept and Ψ_1, \dots, Ψ_7 represents the coefficients of the independent variables Z_1, \dots, Z_7 respectively.

RESULTS AND DISCUSSION

The technical efficiency estimates according to scale of broiler production based on input orientation using the conventional DEA model are presented in Table 1. The estimates are disaggregated into pure technical, overall technical, non-increasing returns assumption, scale efficiency and returns to scale components. Broiler farms operating under small scale, medium scale and large scale produce a mean efficiency of 96, 97 and 98% respectively. This means that given current input bundles and production technology, broiler farmers can potentially retract input use by 4%, 3% and 2% in small scale, medium scale and large scale respectively and still produce the same level of broiler output. The

large scale farms are consistently more efficient than the medium scale farms and the medium scale farms are in turn more efficient than small scale farms across the VRS, CRS and NIRTS assumptions. Todsadee *et al.* (2012) reported 79% as mean TE in broiler in Thailand, Ezech *et al.* (2012) reported 75% in Abia State, Nigeria and Udoh and Etim (2009) also reported 62% in Akwa Ibom, Nigeria. In terms of scale efficiency, majority of farms operate at sub-optimal scale size; 84, 79 and 63% for small, medium and large farms respectively. Thus, a few proportions of the broiler farms produce at optimal scale size; 16, 21 and 37% for small, medium and large farms respectively. We also observed that the majority of the broiler farms produce at increasing returns to scale; 82, 76 and 56% for small, medium and large farms. This means that more production will result to higher marginal returns and subsequently lower marginal costs (Bielik and Rajcaniova, 2004). On the other hand, 18, 24 and 34% of them in small, medium and large scale farms respectively operate at decreasing returns to scale. In line with Bielik and Rajcaniova (2004) this implies that more production will only lead to lower marginal returns and subsequent higher marginal costs. Thus it is rational for farms under increasing returns to scale to increase production while those under decreasing returns to scale to decrease their broiler production.

In Table 2 we present the TE scores estimated under SFA, DEA and bootstrap methods and observe that the TE-SFA are consistently higher than the TE-DEA which are also consistently higher than the TE-Bootstrap under all scale of production. The TE-bootstrap has been corrected for bias; the Bias Technical Efficiency (BTE) is lower than the Bias-Corrected Technical Efficiency (BCTE); indicating the presence of bias in the production. The BCTE estimated in this study is robust. Simar and



Table 1. Technical efficiency in broiler production based on DEA assumption for VRS, CRS, NIRTS, SE and Returns to scale.

TE Range	VRS (OTE)	CRS (PTE)	NIRTS	SE	RTS
Small scale broiler farms					
Very low (0.0000-0.2500)	00(00)	00(00)	00(00)	00(00)	00(00)
Low (0.2501-0.5000)	00(00)	00(00)	00(00)	00(00)	00(00)
High (0.5001-0.7500)	00(00)	00(00)	00(00)	00(00)	00(00)
Very high (0.7501-0.9999)	102(72)	122(87)	117(83)	119(84)	26 DRS
Fully efficient (Exactly 1.0000)	39(28)	19(13)	24(17)	22(16) CRS	93 IRS
Total	141	141	141	141	119
Summary					
Min	0.7895	0.7870	0.7870	0.8394	0.9182
Max	1.0000	1.0000	1.0000	1.0000	1.0000
Mean	0.9611	0.9437	0.9464	0.9823	0.9972
SD	0.0391	0.0441	0.0443	0.0342	0.0109
Medium scale broiler farms					
Very low (0.0000-0.2500)	00(00)	00(00)	00(00)	00(00)	00(00)
Low (0.2501-0.5000)	00(00)	00(00)	00(00)	00(00)	00(00)
High (0.5001-0.7500)	00(00)	00(00)	00(00)	00(00)	00(00)
Very high (0.7501-0.9999)	86(70)	98(80)	97(79)	97(79)	30 DRS
Fully efficient (Exactly 1.0000)	37(30)	25(20)	26(21)	26(21) CRS	67 IRS
Total	123	123	123	123	97
Summary					
Min	0.8769	0.8286	0.8286	0.8358	0.9798
Max	1.0000	1.0000	1.0000	1.0000	1.0000
Mean	0.9678	0.9575	0.9583	0.9894	0.9992
SD	0.0333	0.0389	0.0388	0.0235	0.0024
Large scale broiler farms					
Very low (0.0000-0.2500)	00(00)	00(00)	00(00)	00(00)	00(00)
Low (0.2501-0.5000)	00(00)	00(00)	00(00)	00(00)	00(00)
High (0.5001-0.7500)	00(00)	00(00)	00(00)	00(00)	00(00)
Very high (0.7501-0.9999)	12(38)	21(66)	17(53)	20(63)	11DRS
Fully efficient (Exactly 1.0000)	20(62)	11(34)	15(47)	12(37) CRS	09 IRS
Total	32	32	32	32	20
Summary					
Min	0.9275	0.9056	0.9099	0.9099	0.9668
Max	1.0000	1.0000	1.0000	1.0000	1.0000
Mean	0.9814	0.9703	0.9741	0.9887	0.9960
SD	0.0279	0.0338	0.0312	0.0205	0.0084

Table 2. Distribution of Technical efficiency based on SFA, DEA and Bootstrap estimators.

TE Range	TE-SFA	TE-DEA	TE-Bootstrap (BCTE)	Conf Interval for BCTE	Bias
Small scale broiler farms					
Very low (0.0000-0.2500)	00(00)	00(00)	00(00)	-	-
Low (0.2501-0.5000)	00(00)	00(00)	00(00)	-	-
High (0.5001-0.7500)	00(00)	00(00)	00(00)	-	-
Very high (0.7501-0.9999)	141(100)	102(72)	141(100)	-	-
Fully efficient (Exactly 1.0000)	00(00)	39(28)	00(00)	-	-
Total	141(100)	141(100)	141(100)		
Summary					
Min	0.9307	0.7895	0.7718	0.7448-0.7884	0.0054
Max	0.9961	1.0000	0.9885	0.9811-0.9991	0.0416
Mean	0.9853	0.9611	0.9432	0.9189-0.9599	0.0179
SD	0.0084	0.0391	0.0341	0.0350-0.0384	0.0115
Medium scale broiler farms					
Very low (0.0000-0.2500)	00(00)	00(00)	00(00)	-	-
Low (0.2501-0.5000)	00(00)	00(00)	00(00)	-	-
High (0.5001-0.7500)	00(00)	00(00)	00(00)	-	-
Very high (0.7501-0.9999)	123(100)	86(70)	123(100)	-	-
Fully efficient (Exactly 1.0000)	00(00)	37(30)	00(00)	-	-
Total	123(100)	123(100)	123(100)		
Summary					
Min	0.9428	0.8769	0.8623	0.8306-0.8762	0.0039
Max	0.9972	1.0000	0.9916	0.9846-0.9995	0.0349
Mean	0.9826	0.9678	0.9512	0.9261-0.9669	0.0166
SD	0.0109	0.0333	0.0283	0.0290-0.0333	0.0100
Large scale broiler farms					
Very low (0.0000-0.2500)	00(00)	00(00)	00(00)	-	-
Low (0.2501-0.5000)	00(00)	00(00)	00(00)	-	-
High (0.5001-0.7500)	00(00)	00(00)	00(00)	-	-
Very high (0.7501-0.9999)	32(100)	12(38)	32(100)	-	-
Fully efficient (Exactly 1.0000)	00(00)	20(62)	00(00)	-	-
Total	32(100)	32(100)	32(100)		
Summary					
Min	0.9988	0.9275	0.9203	0.8928-0.9269	0.0064
Max	0.9993	1.0000	0.9868	0.9700-0.9996	0.0236
Mean	0.9991	0.9814	0.9652	0.9301-0.9809	0.0162
SD	0.0000	0.0391	0.0341	0.0350-0.0384	0.0115



Wilson (2000b), Gocht and Balcombe (2006) state that BCTE estimated under bootstrap methodology are free of bias, robust, and reliable. The BCTE are lower than the non-bias corrected estimates; indicating that apart from inefficiency bias in production also cause frontier deviation in broiler production. This is in line with Simar and Wilson (2000b), Gocht and Balcombe (2006). The mean BCTE of 97% is higher than both the medium scale (95%) and small scale (94%). This infers the broiler farmers can potentially withdraw their level of resource use by 6, 5 and 3% in small, medium and large farms respectively and still produce the same level of broiler output with the current technology. This means that it is possible to produce the same output level and still save costs of production as a result of saving some resources. These saved costs or resources could be used to expand production and produce even at a higher output level. Figures 1(a-c) show the plot of the distribution of robust (BCTE) in small, medium and large scale farms respectively. It can be observed that frontier deviation is wider in Table 2; indicating the presence of bias relative to the estimates in Table 1 which did not estimate bias. The bias components indicate the presence of more bias factors in the small farms (1.79%) relative to the medium farms (1.66%) and the large farms (1.62%). Figures 1(d-f) present the plot of distribution of the bias estimates in small, medium and large scale farms respectively. The robustness of the BCTE in this study is validated by its confidence interval at 95% confidence level. Accordingly, BCTE in all the scale of broiler farms is within the lower and upper limits of the confidence interval. The distribution plots of the confidence interval for the small, medium and large scale farms are presented in Figures 2(a-c) respectively. The ANOVA results in Table 3 show that the TE estimates under SFA, DEA and bootstrap estimators are significantly different ($P < 0.01$) in small, medium and large broiler farms respectively. The Bonferroni tests also confirm that the TE

scores between SFA and DEA, SFA and bootstrap, and DEA and bootstrap are significantly different ($P < 0.01$) under small, medium and large broiler farms respectively.

The output elasticity with respect to input use in broiler production in Peninsular Malaysia is presented in Table 4. We found DOC as the most important input that yields output elasticity of 6.29. The result is elastic and means that a percentage increase in DOC/stocking rate will increase broiler production by 6.29%. This finding agrees with Ezeh *et al.* (2012), Emokaro and Emokpae (2014) and Sharafat (2013) who reported 6.24, 1.04 and 1.03 as elasticity for DOC respectively and ranked the DOC as the most important input in broiler production. The second most important input in broiler production in Peninsular Malaysia is medications with output elasticity of 5.99 (elastic), implying a 5.99% increase in broiler output per unit increase in cost of broiler medications. Alabi and Aruna (2005) and Ukwuaba and Inoni (2012) reported 5.15 and 4.58 respectively as production elasticity in broiler. In this study, medications composed of both vaccination and vitamins for the broilers. Medications are crucial in broiler production whether during vaccination or at any period of production, the birds have to be alive and healthy before contributing to output. Medications help to reduce disease infestation and mortality which eventually translate to more production. Similarly, the use of vitamins and other mineral substances in broiler feeds help to boost broiler performance. Utilities is identified as the third most important input with output elasticity of 3.76 also elastic, it means that a 3.76% rise in broiler output will result in 1% increase in cost of utilities. In the context of this study, utilities include cost of water, saw dust, maintenance, electricity, gas and oil for the broiler farms. Except for feeds that exhibit inelastic relationship, all other significant variables (DOC, medications and utilities) exhibit elastic relationship with output elasticity. The feeds with output

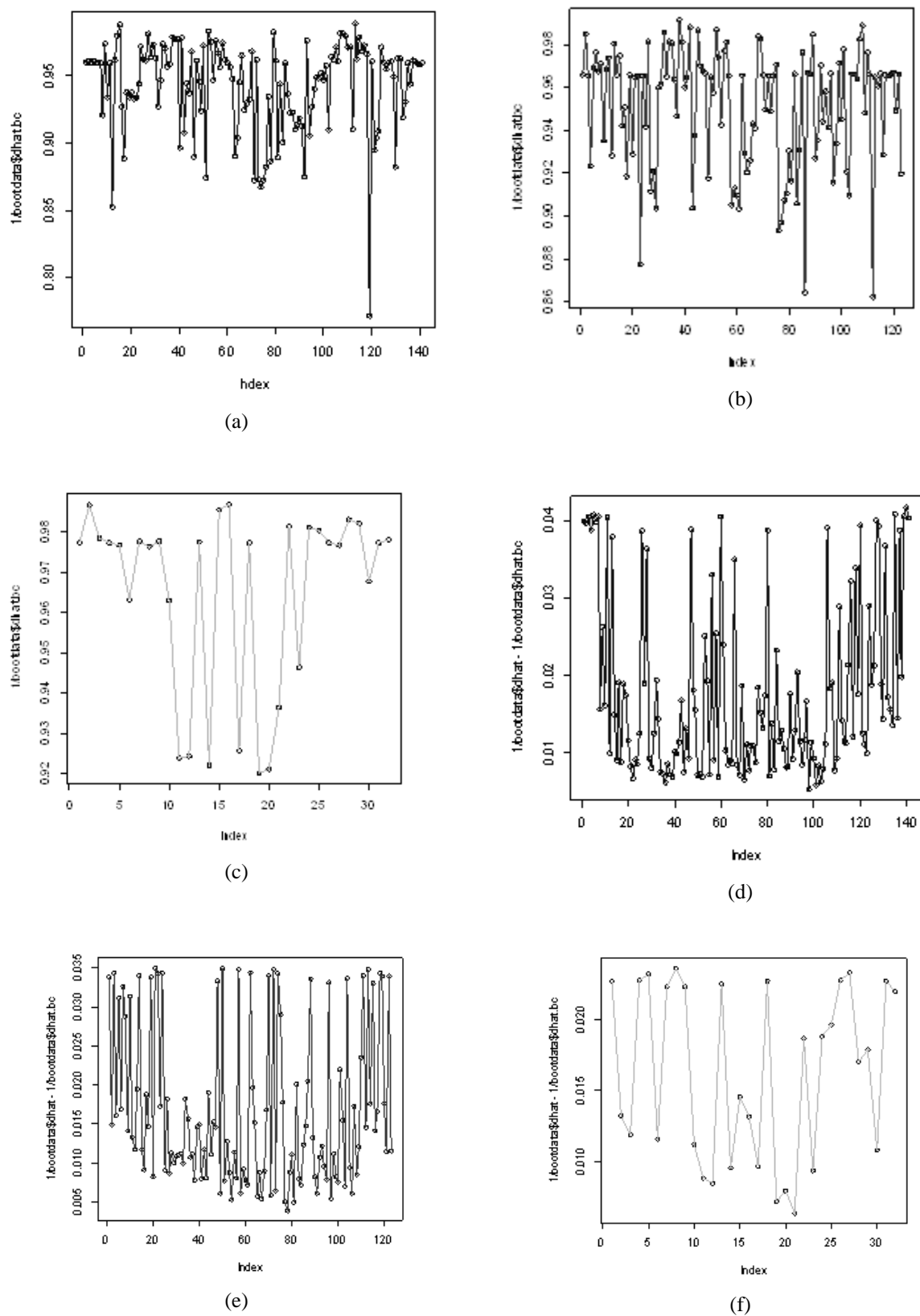
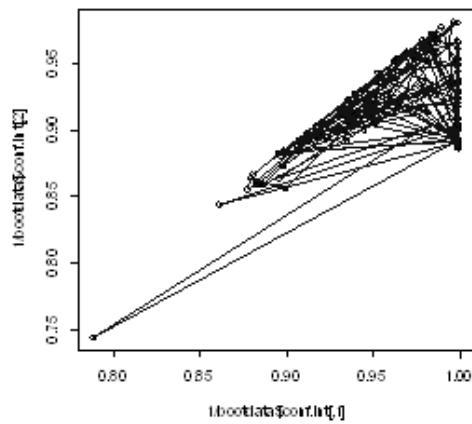
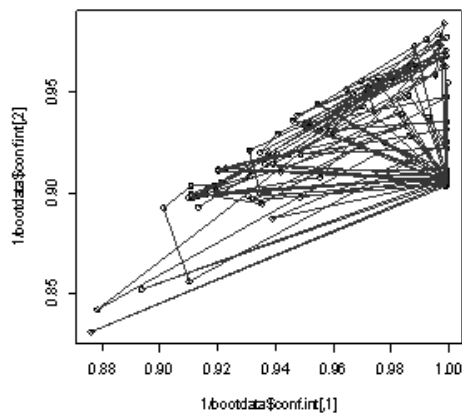


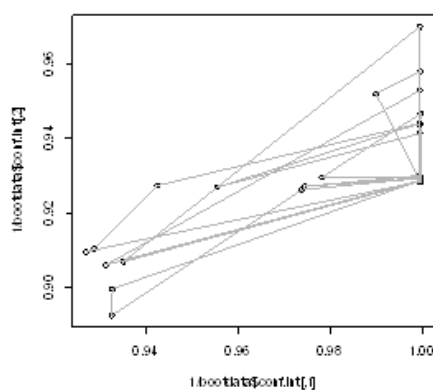
Figure 1. Bias-corrected TE scores for (a) small farms, (b) medium farms, (c) large farms, (d) Bias estimates for small farms, (e) Bias estimates for medium farms (f) Bias estimates for large farms.



(a)



(b)



(c)

Figure 2. TE confidence interval for (a) small farms, (b) medium farms and (c) large farms.

elasticity of 0.09 imply that a percentage increase in feeds will result to a 0.09% increase in broiler output. Udoh and Etim (2009), Emokaro and Emokpae (2014) and Todsadee *et al.* (2012) found 0.56, 0.19 and 0.67 respectively as production elasticity of feeds in broiler production. In general, we estimate a scale elasticity (ϵ) of 16.13 which is greater than 1 ($16.13 > 1$), implying that broiler farms produce under increasing returns to scale. This means that if farmers jointly increase DOC, feeds, medications and utilities by 1%, broiler production will increase by 16.13%. Alabi and Aruna (2005) also estimated a scale elasticity of 12.29%, and Ukwuaba and Inoni (2012) reported scale elasticity of 280.04% in broiler production.

Socio-economic factors affecting technical efficiency in broiler production in Peninsular Malaysia are presented in the Tobit result of Table 5. The BCTE are regressed as the dependent variable against the socio-economic factors as independent variables. Out of the seven (7) independent variables used for the Tobit regression, five (5) are all statistically significant ($P < 0.01$) and with appropriate signs. Experience, age and number of farms owned show negative statistical significance effect on technical efficiency, while education and business status reveal a positive relationship with efficiency. The negative sign on age means that broiler efficiency decreases with age; younger farmers are more efficient than older farmers. This finding is within *a priori* expectation since young farmers are better educated and better exposed to innovative techniques and ideas than the older farmers who are often conservatives. This finding concurs with the findings by Ezech *et al.* (2012) and Esfahene and Khazae (2000).

The negative sign on production experience implies that farmers with more years of production are less efficient than those with few years. This is owing to the fact that farmers with few years of production are mostly younger and hence more educated than the older farmers. It is also likely that some of the older farmers hold on to

Table 3. Results of hypothesis testing for statistical significant difference in technical efficiency under SFA, DEA and Bootstrap estimates.

Parameter	Source	SS	df	MS	F	Sig
H ₀ : SFA≠ DEA≠ BOOTSTRAP in small farms	Between group	0.1261	2	0.0630	68.46	P< 0.01
	Within group	0.3867	420	0.0009		
	Total	0.5128	422	0.0012		
H ₀ : SFA≠ DEA≠ BOOTSTRAP in medium farms	Between group	0.0608	2	0.0304	45.01	P< 0.01
	Within group	0.2474	366	0.0007		
	Total	0.3083	368	0.0007		
H ₀ : SFA≠ DEA≠ BOOTSTRAP in large farms	Between group	0.0183	2	0.0092	20.93	P< 0.01
	Within group	0.0408	93	0.0004		
	Total	0.0591	95	0.0006		

Table 4. Translog result for output elasticity with respect to inputs in broiler production in Peninsular Malaysia.

Variable	Betas	Coefficient	Standard error	t-ratio
DOC (X ₁)	β_1	6.49***	0.69	9.34
Feeds (X ₂)	β_2	3.72***	1.34	2.77
Labour (X ₃)	β_3	-2.07	1.29	-1.59
Medication (X ₄)	β_4	-8.86***	2.03	-4.36
Utilities (X ₅)	β_5	2.69*	1.51	1.78
(DOC) ²	β_6	-1.31***	0.13	-10.04
(Feeds) ²	β_7	0.002	0.22	0.01
(Labour) ²	β_8	-1.15***	0.37	-3.09
(Medication) ²	β_9	-1.63***	0.47	-3.45
(Utilities) ²	β_{10}	-0.78***	0.19	-4.21
DOC×Feeds	β_{11}	-0.81**	0.32	-2.56
DOC×Labour	β_{12}	0.16	0.34	0.49
DOC×Medication	β_{13}	0.69**	0.33	2.12
DOC×Utilities	β_{14}	1.78***	0.40	4.44
Feeds×Labour	β_{15}	0.89**	0.41	2.16
Feeds×Medication	β_{16}	0.23	0.51	0.45
Feeds×Utilities	β_{17}	-2.96***	0.45	-6.57
Labour×Medication	β_{18}	-0.27	0.61	-0.44
Labour×Utilities	β_{19}	1.22**	0.59	2.08
Medication×Utilities	β_{20}	1.88***	0.47	4.00
Intercept	β_0	-7.06***	2.15	-3.29
	Sigma squared	0.008***	0.0007	10.72
	Gamma	0.99***	0.005	180.84
	Log likelihood	482.93		
Output elasticity with respect to				
DOC (X ₁)	Feeds (X ₂)	Labor (X ₃)	Medications (X ₄)	Utilities (X ₅)
6.29***	0.09***	3.35	5.99***	3.76*

Source: Field survey (2013).

**Table 5.** Tobit result for socio-economic factors affecting technical efficiency in broiler production in Peninsular Malaysia.

Variable	Coefficient	Standard error	<i>P</i> > <i>t</i>	Confidence interval
Constant	0.7270***	0.0067	0.000	0.7137 - 0.7402
System	0.0004	0.0017	0.816	-0.0029 - 0.0037
Experience	-0.0038***	0.0003	0.000	-0.0044 - -0.0031
Age	-0.0025***	0.0007	0.000	-0.0038 - 0.0012
Education	0.0058***	0.0002	0.000	0.0054 - 0.0062
Business status	0.0105***	0.0015	0.000	0.0077 - 0.0134
Land status	-0.0011	0.0016	0.503	-0.0043 - 0.0021
Number of farms	-0.0042***	0.0007	0.000	-0.0056 - -0.0029
Sigma	0.0057	0.0002		
Log likelihood	1110.41			

Source: Field survey (2013).

primitive or archaic style of broiler management and as such less efficient. This finding is in agreement with Ezech *et al.* (2012) and Ojo (2003) who stated that experienced farmers hardly devote time supervising their broiler farms due to other engagements hence, leading to lower efficiency. The positive significant sign of education on efficiency infers that better educated farmers are more efficient than less educated ones. The former are expected to have more access to information and technology than the latter and because of more exposure they accept new innovations faster and hence more efficient than less educated farmers. This finding is in concord with the findings of Yusef and Malomo (2007), Begum *et al.* (2010) and Alabi and Aruna (2005).

The study also finds a positive and highly significant relationship between business status of broiler farmers and efficiency. This means that contract farmers are more efficient than non-contract farmers. The contract farmers are bind to contractual agreements as such; they are often extremely committed and dedicated towards fulfilling their agreements. This extreme dedication and commitment results in higher efficiency of the contract farmers compared to the non-

contract farmers. Nguyen *et al.* (2011) stated that the contract farmers are more efficient, less risky and yield higher returns than non-contract farmers in broiler production. Similarly, Chang (2007) stated that contract farming in conjunction with vertical integration is a vital attribute of globally the most efficient broiler farming leading to enhanced production, market efficiency and value added potentials at lower costs.

Finally, the study reveals a negative association between numbers of farm owned and efficiency. This implies that farmers with more farms are less efficient than those with few farms. This is rational since the more the farms a farmer has, the more resources, time and supervision needed thus, leading to a decrease in efficiency and conversely when few or only one broiler farm is owned.

CONCLUSIONS

Although broiler farming is thriving in Malaysia, possibilities for improvement exist with the current resource bundles. Based on the findings of this study, we conclude that inefficiency in broiler

production could be reduced by adjustments in scale efficiency, returns to scale and socio-economic factors (experience, age, education, business status and number of farms). In the short run, farms operating at optimal scale should continue at that level, those at increasing returns and decreasing returns to scale should down-size and up-scale their production respectively. Additionally, farmers should engage in contract farming, own few farms for ease of management and aspire for new knowledge and ideas to explore innovative techniques of broiler management. The foregoing measures will enhance efficiency, productivity and sustainability leading to a competitive atmosphere in the industry for a smooth journey to food security.

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بهره وری قوی و کثش خروجی تولید جوجه های گوشتی در شبه جزیره مالزی

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چکیده

این مطالعه به بررسی مسائل راندمان و کثش تولید جوجه های گوشتی در شبه جزیره مالزی می پردازد. روش های SFA, DEA و bootstrap برای برآورد راندمان فنی، رگرسیون ترویت و ترانسلوگ داده های ۲۹۶ مزرعه استفاده شد تا به ترتیب کثش تولید و تعیین راندمان در تولید جوجه گوشتی محاسبه شود. مشخص شد که میانگین راندمان کشاورزان در زمین های کوچک، متوسط و بزرگ به ترتیب ۹۴٪، ۹۵٪ و ۹۷٪ بود. جدا از ناکارآمدی حداقل bias/noise در تولید جوجه ها دیده شد. نسبت به کثش خروجی، رابطه غیر ارتجاعی در خوراک و ارتجاعی در DOC، دارو ها و آب و برق مشاهده شد. بسیاری از ویژگی های اجتماعی و اقتصادی (تجربه، سن، تحصیلات، وضعیت کسب و کار و تعداد مزارع) رابطه آماری بسیار قابل توجهی با بهره وری نشان می دهد. برای اطمینان از تولید در بازده نهایی بالاتر و هزینه های نهایی کمتر، مزارع تحت افزایش بازده باید تولید را زیاد و مزارع تحت بازده کم نیاز به کم کردن تولید دارند. این مطالعه کشاورزان را به فراگیری علوم مناسب و لازم، کشاورزی قراردادی و مالکیت تعداد کمی مزرعه برای بالابردن راندمان تولید و پایداری صنعت طیور گوشتی، تشویق میکند.