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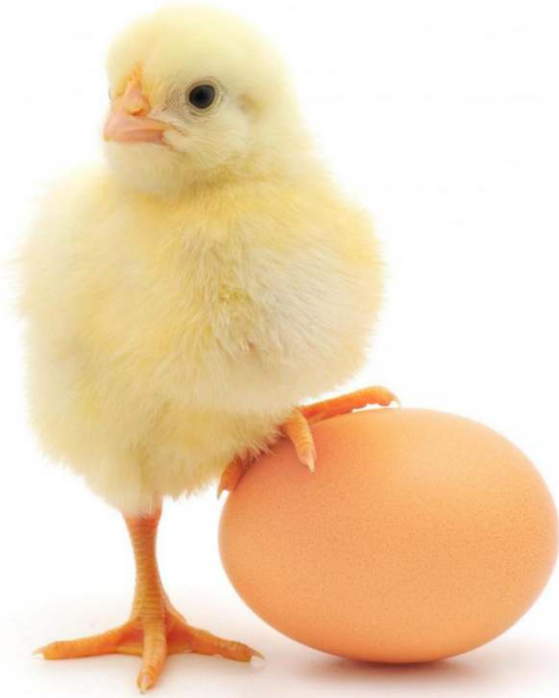

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Research Article
Stochastic Frontier Production Function and Efficiency Status of Poultry Layer Farms in Malaysia

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Abstract
Background and Objective: The high cost of production, in particular feed costs in poultry production, is alarming. This study was conducted to identify patterns of production and sources of waste in resource utilization. **Materials and Methods:** Stochastic frontier production function (SFPF) model was used to measure the output elasticities and investigate the inefficiency effect in Malaysia's poultry layer farms. **Results:** Our findings reveal output elasticities of 1.461 ($p<0.01$), 0.275 ($p<0.10$), 0.048 and -0.130 ($p<0.05$), for day-old chicks (DOCs), labour, operation costs and feeds, respectively; DOCs is the only elastic input and the most important. The results show the presence of approximately 12% noise in poultry egg production. The study revealed overutilization of inputs (input slacks), with feeds (89.46%), labour (39.74%), operation costs (1.40%) and DOCs (1.34%) ranked as the first, second, third and fourth most over utilized inputs, respectively. **Conclusion:** To reduce inefficiency in poultry layer production, inputs should be reduced by the proportion of input slacks evaluated and farmers should strive to operate closed systems of layer production and update their knowledge and skills with the latest production and managerial techniques for improved efficiency and least-cost production. Finally, we recommend that farmers produce at a scale commensurate with the availability of inputs to achieve increases in scale efficiency.

Key words: Layer production, layer farms, feed cost, table eggs, Malaysia

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Data Availability: All relevant data are within the paper and its supporting information files.

INTRODUCTION

Table eggs an essential part of our daily meals; they are a cheap source of protein with several essential nutrients and health benefits. Globally, egg production grew from 51-64 million tons from 2000-2010 but has declined since then[1]. In the year 2000, a total of 5 billion laying flocks produced 51.2 million tons of eggs, which increased to approximately 6.4 billion hens with a production record of 62.1 million tons of eggs in 2009[2]. There are an estimated 6556 million layers (hens) globally, 509 million in Africa, 4211 million in Asia, 765 million in Europe, 1053 million in the Americas and 18 million in Oceania[1]. In general, Asia is ranked first in terms of total output, then the Americas, Europe, Africa and Oceania. China is the world's largest egg producer, with 27.1 million tons produced in 2010 alone[1]. Brunei is the country with the highest individual egg consumption (57.52 kg/person/year in 2007), then Denmark, Japan and the rest. Egg consumption per person per year decreased to 247.7 units from 248.3 units in 2008[2].

Smith[3] reported a production index for table eggs in peninsular Malaysia at 8.57 billion units in 2010, up 11.8% from 7.6 billion in 2009. In the same year, a total of 0.85 million fertile eggs were produced and 59% of those were exported to Brunei. Of the table eggs produced in Malaysia, most (approximately 86%) are for domestic consumption. The remaining 14%, or approximately 1.2 billion, of the table eggs produced in Malaysia in 2010 were exported; 64% of the exports were to Singapore[3]. In terms of the value of production, the 2010 egg production represented RM 2.569 billion (USD 860 million), including exports of RM 346.84 million to obtain a gross profit of RM 85 million (USD 28 million)[3]. Despite these exports, importation of eggs or their products is common in Malaysia. For instance, specific pathogen-free eggs are often imported. Popular layer breeds in Malaysia include Hisex, Lohmann, Novogen and HSH Brown Nick, imported from Germany, the Netherlands and France[3].

Generally, the high cost of poultry production (feed cost) is worrisome. The production costs of eggs relate to the sum of all variable and fixed costs incurred in producing a given number of eggs. In view of the continued high costs of layer production and the frugality of consumers, future growth will probably slow down in the layer sub-sector to approximately 1% in a year[1]. A mixture of high feed costs, legislation and the ban on cages and other peculiarities around the globe has put the cost of egg production at the highest rate ever[4]. Furthermore, feed is the costliest input in egg production and when the feed costs for the pullets are included, the share of feed to total production cost can reach 70%[4]. In addition, layer farms in Europe changed their housing structure for layers to enriched cages and aviaries, which further increased the cost of housing and labour per hen. Feed cost is a universal reason for the increase in costs of production in poultry layers but nations may vary in peculiarities for other additional costs of production. Ariffin *et al.*[5] states that the poultry industry in Malaysia is faced with many challenges, including the cost of feeds, which comprises approximately 70% of production costs. High feed costs from farms adds substantially to the burden of production costs. There are many quality control issues in egg production in Malaysia and of immediate interest is the issue of feed adulteration[6]. The issues of feed adulteration and feed waste during production both add to the high cost of production. Despite the investment in poultry egg production in Malaysia, not much is known about its production patterns and resource use efficiency. Given the high production costs, this research employs a stochastic frontier approach (SFA) model to estimate the output elasticities of production and examine the inefficiency effect model. In addition, a scale-based model of technical efficiency (SBMTE) is also used to investigate the excessive input utilization (input waste) in poultry layer production. Finally, the bootstrap technique is used to simulate the bias-corrected technical efficiency (BCTE) and examine scale efficiency and returns to scale in production.

MATERIALS AND METHODS

Data collection: Data for this study was collected from a total of 96 layer farms in peninsular Malaysia. Simple random sampling was used in the selection of the layer farms in the major producing states of Negeri Sembilan, Johor, Penang, Melaka, Pahang, Selangor and Kedah. A total of one output (Number of eggs) and four (4) inputs (Feeds, Operation cost, Labour and total day-old chicks) were used in the analysis. Detailed descriptions of the production and inefficiency variables used in this study are presented in Table 1.

Analytical techniques

Stochastic frontier production function (SFPF): The generalized form of the SFPF, originally developed by Aigner *et al.*[7] and Meeusen and Van den Broeck[8] and refined by Battese and Coelli[9,10], is adopted to assess the production frontier and inefficiency issues in the layer farms. It is as follows:

$$Y_i = f(X_i, \alpha_i) \exp(\varepsilon_i) \quad (1)$$

Table 1: Description and mean values of variables used in the study

Variables	Description	Unit	Mean
Production variables			
Output	Total eggs produced	Number	893971.40
Feeds	Quantity of feeds used	Kilogram	220931.70
Operation costs	Costs of variable inputs	Ringgit*	97889.35
Labour	Total labour utilized	Man-hours	1564.02
Day-old chicks (DOCs)	Total DOCs purchased	Number	95114.00
Inefficiency variables			
Age	Age of farmers	Years	46.56
Education	Educational status (1= tertiary education; 0 other)	-	0.34
Experience	Years of production experience	Years	27.93
Farm ownership	Farms owned (1= one farm; 0 other)	-	0.85
Production system	System (1 = closed; 0 other)	-	0.45
Mortality rate	Rate of birds' mortality	Rate (%)	3.89
Number of coops	Number of coops owned by farmer	Number	18.80

*Malaysian currency (1 USD: 4.2 Ringgit)

Table 2: Hypotheses tests for model specification and statistical assumptions

Null hypotheses	Test statistics	Critical values	Decision
H_0: $\beta_{ij} = 0$ (2nd-order coefficients are zero, or the cobb-douglas function better fits the data)	40.250	17.670	Reject H_0
H_0: $\gamma = \delta_0 = \delta_1 = \cdots \delta_7 = 0$ (Inefficiency is absent in the model)	199.886	16.274	Reject H_0
H_0: $\delta_1 = \delta_2 = \cdots \delta_7 = 0$ (Farm-specific factors do not influence inefficiency)	17.940	13.401	Reject H_0

where, Y_i is egg output, X_i is matrix of inputs and α_i is a vector of parameter to be estimated. The error term (ε_i) is made up of two components V_i and U_i which are related as $\varepsilon_i = V_i - U_i$. V_i accommodates random variations in the output that are caused by factors beyond farmers' control and the effects of errors of measurement in the output variable[11]. In contrast, U_i is a random variable that handles stochastic shortfall in outputs relative to the most efficient decision-making unit (DMU)[9].

Thus:

$$Y_i = f(X_i, \alpha_i) \exp(V_i - U_i) \qquad (2)$$

V_i is normally distributed with mean and variance $= \delta_v^2$. U_i is a truncated normal distribution with mean $\rightarrow U_i = \delta_0 + \sum_{j=1}^{J} \delta_j Z_{ji}$ and variance $= \delta^2$. Note that Z_{ji} represents the value of the j_{th} explanatory variable related with the technical inefficiency model of the DMU and $\delta_0 \cdots \delta_j$ are unknown parameters that are to be estimated. Parameters of both the stochastic frontier model and the inefficiency effects are jointly estimated in a single step solution with the maximum likelihood estimation technique. Parameters of variance in the likelihood function are estimated from the study of Battese and Coelli[9] as:

$$\delta_s^2 = \delta_v^2 + \delta^2 \text{ and } = \frac{\delta^2}{\delta_s^2}$$

Functional form specification: We use both the Cobb-Douglass and translog functional forms in this study. The Cobb-Douglass is a special form of the translog function known for its disadvantage of strict restrictions on production technology by specifically limiting elasticities of production to be constant and elasticities of inputs to be 1. We therefore tested the Cobb-Douglass function against the translog function to determine whether it was sufficient enough to represent the data and we obtain conclusive evidence that it indeed is not (Table 2). Hence, the Cobb-Douglass function is discontinued from further consideration in this study. The functional form specification for the translog[9] is presented below:

$$\ln Y_i = \beta_0 + \sum_{j=1}^{4} \beta_j \ln X_{ij} + 0.5 \sum_{j=1}^{4} \sum_{k=1}^{4} \beta_{jk} + \ln X_{ji} + \ln X_{ki} + (V_i - U_i) \qquad (3)$$

Where

Y_i = No. of eggs

X_1 = Quantity of feed used (kg)

X_2 = Operation costs (RM)

X_3 = Labour (person-hours)

X_4 = Total day-old chicks (DOCs)

Slack-based measure of technical efficiency (SBMTE): Since the advent of data envelopment analysis (DEA) in 1978, several modifications have been developed to overcome some perceived limitations. The DEA models are of two kinds: radial and non-radial. The Charnes-Cooper-Rhodes (CCR) model is a typical radial model, while the slack-based measure (SBMTE) is typically a non-radial measure[12]. The radial approach differs from the non-radial in two ways. First, the radial model assumes that inputs and outputs (q) change proportionately, while the non-radial (SBMTE) model assumes that some inputs can be substituted and, as such, exhibit non-proportional change. Second, the radial approach does not capture slack but the non-radial approach (SBMTE) handles slack. From the intuition of Charnes *et al.*[13] on the development of the additive DEA model, Tone[14] non-radial model; the slack-based model of technical efficiency (SBMTE). Torgersen *et al.*[15] stated that the SBMTE estimates scores that are unit invariant, monotonic and reference-set dependent[16], which impedes the influence of outliers or extreme observations on the efficiency scores. In this study, the non-radial (SBMTE)-input oriented approach in line with Tone[14] is adopted, as below:

To assess the relative efficiency of $DMU_0 = (x_0, y_0)$, the following linear program needs to be solved[14]. This step is then repeated n times for 0 = (1,..., n):

$$\rho_I^* = \min_{\lambda, s^-, s^+} 1 - \frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{i0}} \tag{4}$$

Subject to:

$$x_{i0} = \sum_{j=1}^{n} x_{ij}\lambda_j + s_i^- \; (i=1,\ldots,m),$$

$$y_{r0} = \sum_{j=1}^{n} y_{rj}\lambda_j - s_r^+ \left(r=1,\ldots,s\right)$$

$$\lambda_j \geq 0(\forall_j), s_i^- \geq 0(\forall_i), s_r^+ \geq 0(\forall_r)$$

where, ρ_I*denotes SBMTE-input, n is the number of DMUs (96), m is the number of inputs (4), s is the number of outputs (1), s_i excess, s_r^+ is output shortfall and λ_j is a non-negative vector that permits the construction of the production possibility set for j DMU. Furthermore*,* x_{ij} (m is feeds, operation costs, labour and day-old chicks) and y_{rj} (s is number of eggs). Note that if ρ_I*=1 → efficient level, meaning that both the ($s_i^{-*} = 0$) and output shortfall ($s_i^{+*} = 0$) for all i and r entries are zero.

DEA-bootstrapping methodology for robust technical efficiency estimation: The application of bootstrapping in efficiency measurement is premised on one of the major shortcomings of the DEA estimator. Linh[17] asserts that DEA results lack statistical properties, which results in biased and spurious estimates. Simar and Wilson[18] assert that applying the bootstrapping method is currently the most feasible approach for establishing a consistent statistical property for a DEA estimator; subjecting the DEA scores to further estimation allows us to obtain a more robust and reliable DEA score through bootstrapping. Bootstrapping entails generating a new set of data by simulating the original data using a given number of iterations. It is a simulation method that involves Monte Carlo estimation. The Monte Carlo method is used in bootstrapping to simulate the data-generating process (DGP) to produce a valid estimator; it tests and confirms the presence of stochastic effects in observations via bias and the confidence interval for the bias-corrected scores[19]. The procedure for executing the homogenous smoothed bootstrap methodology is shown below.

Assume you are given a DMU, and input-output data, (x_k, y_k). If k = 1,...,n, compute $\hat{\theta}_k$ with a linear programming approach to estimate efficiency. 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, $\theta_1^*,\ldots,\theta_n^*$, for i = 1,..., n are obtained by making $\beta_1^*,\ldots,\beta_n^*$, a simple bootstrap sample derived by drawing with replacement. Thus, a random sample size can be obtained as follows[19]:

$$\tilde{\theta}_i^* = \begin{Bmatrix} \beta_i^* + h\varepsilon_i^* \text{ if } \beta_i^* + \varepsilon_i^* \leq 1 \\ 2 - \beta_i^* - h\varepsilon_i^* \text{ otherwise} \end{Bmatrix} \tag{5}$$

and the corrected bootstrap sample is obtained via:

$$\theta_i^* = \frac{\bar{\beta}^* + 1}{\left(\frac{\sqrt{1+h^2}}{\hat{\delta}_{\hat{\delta}}^2}\right)\left(\tilde{\theta}_i^* - \bar{\beta}^*\right)} \tag{6}$$

Where

$$\bar{\beta}^* = 1/n\sum_{i=1}^{n}\beta_i^*, \hat{\delta}_{\hat{\theta}}^2$$

denotes the sample variance of $\theta_1^*,\ldots,\theta_n^*$, is the bandwidth factor and ε_i^* is a random deviate. In accordance with the work of Simar and Wilson[18] on the computation of the bandwidth factor, we suggested the use of normal reference rule and set the bandwidth as $h = 1.06\hat{\delta}_{\hat{\theta}}^2 n^{-1/5}$ for a normally distributed data set $(\hat{\theta})$. Furthermore, they suggest the use of least-square cross validation that relies on a choice of bandwidth that has the minimal approximation ability of the mean integrated square 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 is used.

Use the smoothed bootstrap sample sequence above to compute the new data

$$\left\{\left(x_{ib}^*, y_i\right) | i=1,...,n\right\} \text{ where, } x_{ib}^* = \left(\frac{\tilde{\theta}_i}{\theta_{ib}^*}\right) x_i, \{i=1,...,n\} \quad (7)$$

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

$$\hat{\theta}_{k,b}^* = \min\left\{\theta > 0 \mid y_k \le \sum_{i=1}^{n} \gamma_i y_i | \theta_{x_k} \ge \sum_{i=1}^{n} \gamma_i x_i^*, \; b \mid \sum_{i=1}^{n} \gamma_i = 1, \gamma_i \ge 0, i=1.,n\right\} \quad (8)$$

Steps 2-4 are iterated B times to provide for k = 1,...n a set of estimates $\left\{\hat{\theta}_{k,b}^* \; b=1,...,B\right\}$. Simar and Wilson[20] recommend a minimum of 2000 bootstrap iterations; in line with that suggestion, we also set 2000 iterations for the simulation. Note that the bootstrap efficiency scores $\hat{\theta}_k^*$ and DEA efficiency scores $\hat{\theta}_k$ represent approximations of $\hat{\theta}_k$ and θ_k, respectively.

RESULTS AND DISCUSSION

Tests of hypotheses: We used the generalized likelihood ratio (LR) to test the null hypothesis that the second-order and interaction variables in the transcendental function are zero (H_0: $\beta_{ij} = 0$). This hypothesis implies that the log-linear (Cobb-Douglass) function better explains the phenomena of poultry egg production than the transcendental function. However, this hypothesis, as presented in Table 2, is rejected following an estimation of the LR statistic (= 40.25), which is higher than the critical value (= 17.670) in Kodde and Palm[21]. The rejection of the null hypothesis suggests that the transcendental function better fits and more appropriately explains the production scen eggs in Malaysia than the Cobb-Douglass function. Hence, the transcendental function results were chosen and presented to derive the conclusions of this study. Studies such as those of Ashagidigbi *et al.*[22] and Adeyonu *et al.*[23] also concur in the selection of the translog function over the Cobb-Douglass function in describing the scenario of poultry egg production.

In addition to the first hypothesis on the selection of functional form, as explained earlier, Table 2 also presents the other important hypotheses of the study. The second null hypothesis portrays the absence of technical inefficiency in the model (H_0: $\gamma = \delta_0 = \delta_1 = ... \delta_7 = 0$). Failing to reject this hypothesis indicates the absence of technical inefficiency in the poultry layer production. This further suggests that the ordinary least square (OLS), a measure of traditional average response function that assumes all farmers are technically efficient, would have been adequate to describe the data in this study. Nevertheless, the hypothesis is also rejected owing to a higher LR (199.886) relative to critical value (16.274). Thus, there is presence of technical inefficiency in the model, hence the need to identify the sources of inefficiency in the poultry layer production system. We use the third hypothesis to test whether or not farm-specific factors are truly a source of inefficiency in poultry layer production. The null hypothesis is that coefficients of variables incorporated in the inefficiency model, precluding the intercept, are zero (H_0: $\delta_1 = \delta_2 = ... \delta_7 = 0$). This scenario, as observed by Stevenson[24], asserts that the impacts of technical inefficiency assume a truncated-normal distribution with a mean not equal to zero. This hypothesis is also incorporated, suggesting that the joined effects of the factors incorporated in the technical inefficiency model are significant (LR = 17.940> the 13.401 critical value).

Estimated parameters of the SFPF: Table 3 presents the maximum likelihood estimates (MLE) of the Stochastic Frontier Model. With the exception of feeds, the coefficients of parameters estimated in the SFPF have the expected positive signs; feeds (-), operating costs (+), labour (+) and DOCs (+). However, operating cost is the only input that did not show statistical significance, while the others show varying levels of significance; feeds (p>0.05), labour (p>0.10) and DOCs (p>0.01). In this study, the first-order parameters are interpreted as output elasticities. Coelli *et al.*[25] stated that if data is subjected to mean correction, then the first-order coefficients can be interpreted as output elasticities. Thus, output elasticity with respect to day-old chicks (DOCs) was the highest (1.461); this means an increase in DOCs by 1% increases egg output by 1.461%. Nmadu *et al.*[26], Adeyonu *et al.*[23], Adedeji *et al.*[27] and Adepoju[28] also found a similar positive correlation between DOC and egg output. As the second most important input, labour has 0.275 output elasticity and was significant (p>0.10). This means that a 1% increase in labour increases egg output by 0.275%. This finding concords with those of Adeyonu *et al.*[23] and Adedeji *et al.*[27], who also found a positive correlation between

Table 3: Maximum likelihood estimates of the SFPF (translog) and inefficiency models of poultry eggs

Variables	Parameters	Coefficients	Standard error	T-ratios
Stochastic frontier model				
Constant	β_0	0.122	0.437	0.281
Feeds (X_1)	β_1	-0.130‡	0.072	-1.799
Operating costs (X_2)	β_2	0.048	0.534	0.089
Labour (X_3)	β_3	0.275§	0.176	1.565
DOC (X_4)	β_4	1.461†	0.560	2.620
$(X_1)^2$	β_5	-0.006§	0.004	-1.432
$(X_2)^2$	β_6	-0.233	0.292	-0.796
$(X_3)^2$	β_7	-0.023	0.033	-0.698
$(X_4)^2$	β_8	-0.290	0.352	-0.825
$(X_1 X_2)$	β_9	0.056	0.057	0.971
$(X_1 X_3)$	β_{10}	0.008	0.020	0.400
$(X_1 X_4)$	β_{11}	-0.024	0.054	-0.446
$(X_2 X_3)$	β_{12}	0.053	0.116	0.452
$(X_2 X_4)$	β_{13}	0.456	0.640	0.713
$(X_3 X_4)$	β_{14}	-0.092	0.116	-0.792
Inefficiency effect model				
Age	δ_1	-9.524×10^{-4}	5.962×10^{-3}	-0.160
Education	δ_2	-0.064†	0.024	-2.690
Production experience	δ_3	-0.005†	0.001	-4.428
Number of farms owned	δ_4	-0.005	0.024	-0.225
Type of production system	δ_5	-0.031§	0.021	-1.466
Mortality rate	δ_6	7.125×10^{-3}‡	3.620×10^{-3}	1.968
Number of coops	δ_7	-0.006‡	0.003	-1.874
Sigma square	δ^2	0.003†	3.550×10^{-3}	7.719
Gamma	γ	0.999†	2.036×10^{-3}	4.913×10^4
Log-likelihood ratio		164.430		
Mean TE		0.8858		

†: 1% level of statistical significance, ‡: 5% level of statistical significance, §: 10% level of statistical significance

labour and egg production. However, studies conducted by Adeyonu *et al.*[23], Afolabi *et al.*[29] Ashagidigbi *et al.*[22] and Nmadu *et al.*[26] identified a negative association owing to over utilization of labour. Next is operating costs, which has a 0.048 output elasticity but is not significant, denoting a 0.048% increase in egg output from a 1% increase in operating costs. Adepoju[28] and Ojo[30] also reported positive coefficients of operating costs on poultry layer egg production in their studies.

In contrast, feed is inversely proportional to egg output; its coefficient (-0.130) implies that a 1% increase in feed reduces egg production by 0.130%. This negative sign indicates over utilization or waste of feed in layer farms. This negative sign is consistent with many poultry egg studies. For instance, Ojo[30], Adepoju[28], Ashagidigbi *et al.*[22] and Adeyonu *et al.*[23] found negative coefficients of feed and stated its non-optimal use as the cause of the negative relationship. A scale elasticity of 1.654 is estimated (summation of output elasticities) and since 1.654>1, on average, the layer farms produce at increasing returns to scale (IRS) or stage 1 of the production function, which further implies that farms are not scale efficient. By implication, if the layer farms jointly increase all factor inputs (feed, operating costs, labour and DOCs) by 1%, then egg output will increase by 1.654%, *ceteris paribus*. The finding that poultry layers produce at stage 1 agrees with the finding of Adedeji *et al.*[27] but is in contrast with that of Nmadu *et al.*[26] and Afolabi *et al.*[29].

Estimated parameters of the inefficiency model: All the variables included in the inefficiency model present the expected negative signs except mortality but only five out of the seven are statistically significant. Education is (-) and significant (p>0.01); this indicates that higher education decreases technical inefficiency since new knowledge and skills are developed for better management of farms. This agrees with Akinyemi *et al.*[31], Yusuf and Malomo[32], Ashagidigbi *et al.*[22] and Adepoju[28]. Production experience is (-) and significant (p>0.01); this also indicates that higher production experience reduces inefficiency. These findings show that poultry (layer) farmers learn to improve on their production deficiencies for better production over time. Production experience in itself is another form of education for the farmer, has to learn and adjust for improved productivity. Adeyonu *et al.*[23] and Ashagidigbi *et al.*[22] found in their studies a negative relationship between production experience and inefficiency in layer production. The number of coops owned is (-) and significant (p>0.05); this indicates that inefficiency decreases with the acquisition of more coops on the farm. The number of coops owned on a layer farm depends on the number of chicks reared. The more coops there are, the greater the layer stock (birds) is and vice versa. This corroborates Adedeji *et al.*[27], who also revealed a negative correlation between DOCs and inefficiency.

As in the broiler sub-sector, there are two types of production systems in layer farms; closed and open systems. Thus, the negative sign and significance (p>0.10) level indicates that inefficiency could be reduced by operating a closed system of production and conversely. Under the closed system, the layers receive better management in terms of regulating the environment, which helps to reduce mortality and ultimate reductions in inefficiency. Similarly, lower mortality of the layers reduces inefficiency evident from the positivity and significance (p>0.05). Egg production depends on the number of layer stock; lower mortality indicates insignificant reduction in the layer stock and this aids in reducing inefficiency. In contrast, higher mortality reduces the number of layer stock and egg production which ultimately results in higher inefficiency. Other farm-specific variables with appropriately negative signs but which were not significant, are age and total number of layer farms owned.

The result of the slack-based model (SBM) for the radial measure of excess input utilization or slack is presented in Table 4. The input slack shows feed, labour, operation costs and DOCs with mean slacks of 89.46, 39.74, 1.40 and 1.34, respectively. This means that feed, labour, operation costs and DOCs are over-utilized by 89.46, 39.74, 1.40 and 1.34%, respectively. This f could be withdrawn from the production process by their respective proportion and the output of eggs will remain unchanged. Ranking of input slack shows feed, labour, operation costs and DOCs, with ranks of 1, 2, 3 and 4, respectively, as the most over-utilized inputs in decreasing order. If these input slacks were monetized based on the prices of the inputs on individual farms affected, then the amount could be quite substantial on some farms. Their reduction will help save production costs and, eventually, attain technically efficient levels (frontiers).

(BTE) and the bias-corrected technical efficiency (BCTE) scores in the layer farms; the BCTE is lower than the BTE, which indicates the presence of production noise. Having adjusted for bias, the BCTE scores are robust estimates[19]. The BCTE of the layer farms ranges between 0.1613 and 0.8784, with a mean of 0.5745. On average, the layer farms operate at 57.45% efficiency; in other words, the layer farms are 42.55% technically inefficient. By implication, possibilities abound for production inputs in the layer farms to be reduced by 42.55% without any loss in total output (egg production). The maximum and minimum values are wide in range, suggesting wide variations in the level of input use and output among the poultry layer farms in Malaysia (Table 5). The level of inefficiency in the layer sub-sector is high and indeed worrisome but indicates the level of adjustment needed for judicious and improved egg production. We also observed the confidence interval, a means of testing the hypothesis for the BCTE scores, which shows a mean BCTE (0.5745) lying between the lower mean (0.4958) and the upper mean (0.6796) confidence interval. The bias estimates range

Table 4: Input slacks in poultry egg production in Malaysia

	Input slacks (%)			
	Feeds (X_1)	Operation costs (X_2)	Labour (X_3)	Day-old chicks (X_4)
Mean slacks	89.46	1.40	39.74	1.34
Ranking	1	3	2	4

Table 5: Distribution of BTE, BCTE and bias in poultry layer production in Malaysia

TE range	TE-SFA	BTE	BCTE	Conf. Interval for BCTE	Bias
Efficiency range					
Very low (0.0000-0.2500)	0(0.00)	0(0.00)	0(0.00)	-	-
Low (0.2501-0.5000)	0(0.00)	0(0.00)	0(0.00)	-	-
High (0.5001-0.7500)	2(2.08)	4(4.17)	8(8.33)	-	-
Very high (0.7501-0.9999)	94(97.92)	64(66.67)	88(91.67)	-	-
Fully efficient (exactly 1.0000)	0(0.00)	28(29.17)	0(00)	-	-
Total	96(100)	96(100)	96(100)		
Summary					
Min	0.6822	0.1956	0.1613	0.1423-0.1922	0.0305
Max	0.9999	1.0000	0.8784	0.8135-0.9850	0.2626
Mean	0.8858	0.6929	0.5745	0.4958-0.6796	0.1183
SD	0.0670	0.2494	0.1910	0.1613-0.2443	0.0693

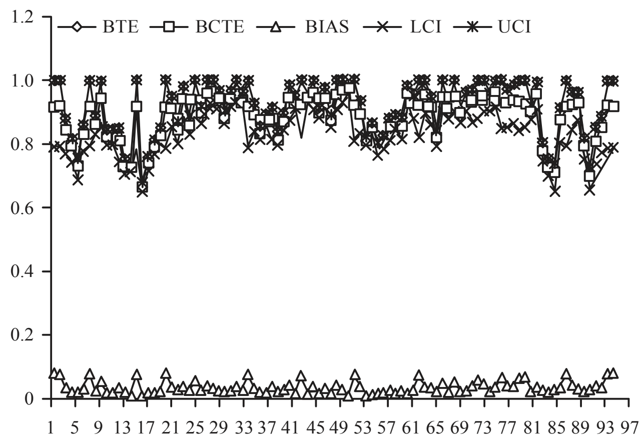

Fig. 1: Trend of efficiency indicators of poultry layer farms in Malaysia based on 2000 bootstrap iterations

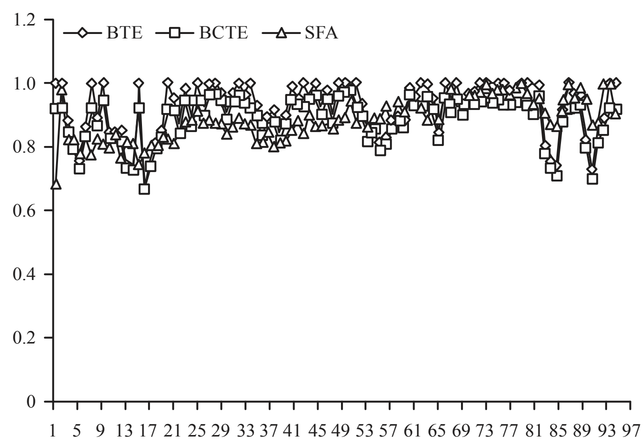

Fig. 2: Trend of technical efficiency estimates under BTE, BCTE and SFA estimators

Table 6: Scale efficiency and returns to scale based on the DEA model in poultry layer farms

Scale efficiency (SE)	Returns to scale (RTS)
Scale efficient farms = 21(21.00)- Optimal	DRS farms = 26(28.00)-Super optimal
Scale inefficient farms = 75(79.00)-Non-optimal	IRS farms = 49(51.00)-Sub-optimal
Total 96 (100)	Total = 75(79.00)
Mean SE 0.938	

between 0.0305 and 0.2626, with a mean of 0.1183; this indicates the presence of 11.83% noise on average in the Malaysian poultry layer sub-sector. Figure 1 and 2 show the trend of efficiency indicators estimated at 2000 boots and the trend of technical efficiency estimates under BTE, BCTE and SFA estimators, respectively.

Table 6 shows the scale efficiency and returns to scale status based on the DEA model in poultry layer production. Approximately 21 (21%), 26 (28%) and 49 (52%) of the layer farms produce constant (CRS), decreasing (DRS) and increasing (IRS) returns to scale, respectively. In other words, only 21% of the farms are scale efficient or produce at optimal levels, while 52 and 28% produce at sub-optimal and super-optimal levels, respectively. In line with Padilla-Fernandez and Nuthall[33], production at an appropriate scale is recommended in the Malaysian layer sub-sector. Accordingly, farms producing at an optimal scale should maintain the use of current inputs, those at sub-optimal scale should produce at higher levels of inputs and those at super-optimal scale should reduce input levels, at least in the short term, to gain the benefit of high marginal returns and low marginal costs.

CONCLUSION

We used a holistic approach including stochastic production frontier, slack-based model of technical efficiency and robust bootstrap simulation techniques in the efficiency analyses of layer farms in Malaysia. The key findings of the study include the following. The study finds day-old chicks to be the only elastic and most important input in layer production. In addition, the study estimates 69% as the mean bias technical efficiency, 57% as the bias-corrected technical efficiency and a noise effect of approximately 12%. Furthermore, the study revealed that 90% of feed and 40% of labour inputs in layer production are over utilized. Thus, only 21% of layer farms are optimal, 28% are super-optimal and 51% are sub-optimal. Finally, inefficiency can be improved with education, production experience, production systems and number of coops.

Despite the significant contributions of the poultry layer sub-sector to the economy of Malaysia, the results in this study reveal that much needs to be done to improve the efficient resource utilization of this section and to reach a more competitive level. To minimize inefficiency and enhance productivity in layer production, the following measures are imperative. On average, farmers should curtail waste in feeds by almost 90% and labour by almost 40%; this will improve input slack and, ultimately, efficiency. Farmers should also aspire to more education (knowledge, techniques or skills) in layer production and operate a closed system of production; this will reduce the effects of inefficiency and, ultimately, the efficiency itself. To achieve frontier production in layer farms, production at an appropriate scale is also imperative. Optimally producing farms should continue production with their current input bundles. Similarly, sub-optimal farms should increase their input bundles, while super-optimal farms should decrease their input bundles in production to attract high marginal returns and low marginal costs.

SIGNIFICANCE STATEMENT

This study focuses on identifying the inefficiency problem of layer production in Malaysia. This study will assist farm management in reducing inefficiency levels in the inputs of production and lead to proper scale efficiency. Hence, the new theory of stochastic frontier production and the efficiency status of poultry farms in Malaysia may be obtained.

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REFERENCES

1. Poultry Site, 2013. Global poultry trends: World egg production set a record despite slower growth. http://www.thepoultrysite.com/articles/2653/global-poultry-trends-world-egg-production-sets-a-record-despite-slower-growth/.
2. Wattagnet, 2010. Watt executive guide to world poultry trends. https://www.wattagnet.com/ext/resources/ uploaded Files/WattAgNet/Footer/Footer_Content/2010_ Poultry_ Trends.pdf
3. Smith, A., 2011. Malaysian egg market set for continued growth. https://www.wattagnet.com/articles/10203-malaysian-egg-market-set-for-continued-growth
4. Van Horne, P., 2013. Production costs of eggs at record high level. World Poultry. https://www.poultryworld.net/Eggs/Articles/2013/10/Production-costs-of-eggs-at-record-high-level-1315811W/
5. Ariffin, A.S., S. Mohtar and N.H. Baluch, 2014. Broiler industry with emphasis on short supply chain in Malaysia. Proceedings of the 4th International Conference on Technology and Operations Management, August 18-19, 2014, Kuala Lumpur, Malaysia, pp: 34-46.
6. Raghavan, V., T. Chandran and S.H. Chan, 2002. Problems encountered in Malaysian egg production and quality. World Poult., 18: 26-29.
7. Aigner, D., C.A.K. Lovell and P. Schmidt, 1977. Formulation and estimation of stochastic frontier production function models. J. Econometrics, 6: 21-37.
8. Meeusen, W. and J. van den Broeck, 1977. Efficiency estimation from Cobb-Douglas production functions with composed error. Int. Econ. Rev., 18: 435-444.
9. Battese, G.E. and T.J. Coelli, 1995. A model for technical inefficiency effects in a stochastic frontier production function for panel data. Empir. Econ., 20: 325-332.
10. Battese, G.E. and T.J. Coelli, 1993. A stochastic frontier production function incorporating a model for technical inefficiency effects. Working Papers in Econometrics and Applied Statistics No. 69, Department of Econometrics, University of New England, Armidale.
11. Villano, R.A. and E.M. Fleming, 2004. Analysis of technical efficiency in a rainfed lowland rice environment in central Luzon Philippines using a stochastic frontier production function with a heteroskedastic error structure. Working Papers 12906, University of New England, School of Economics.
12. Tone, K., 2011. Slacks-Based Measure of Efficiency. In: Handbook on Data Envelopment Analysis, Cooper, W.W., L.M. Seiford and J. Zhu (Eds.). Springer Science+Business Media, USA., pp: 195-210.

13. Charnes, A., W.W. Cooper, B. Golany, L.M. Seiford and J. Stutz, 1985. Foundations of data envelopment analysis for pareto-koopmans efficient empirical production functions. J. Econometr., 30: 91-107.
14. Tone, K., 2001. A slacks-based measure of efficiency in data envelopment analysis. Eur. J. Operat. Res., 130: 498-509.
15. Torgersen, A.M., F.R. Forsund and S.A.C. Kittelsen, 1996. Slack-adjusted efficiency measures and ranking of efficient units. J. Prod. Anal., 7: 379-398.
16. Banker, R.D., A. Charnes and W.W. Cooper, 1984. Some models for estimating technical and scale Inefficiencies in data envelopment analysis. Manage. Sci., 30: 1078-1092.
17. Linh, V.H., 2012. Efficiency of rice farming households in Vietnam. Int. J. Dev. Issues, 11: 60-73.
18. Simar, L. and P.W. Wilson, 2000. A general methodology for bootstrapping in non-parametric frontier models. J. Applied Stat., 27: 779-802.
19. Gocht, A. and K. Balcombe, 2006. Ranking efficiency units in DEA using bootstrapping an applied analysis for Slovenian farm data. J. Agric. Econ., 35: 223-229.
20. Simar, L. and P.W. Wilson, 1998. Sensitivity analysis of efficiency scores: How to bootstrap in nonparametric frontier models. Manage. Sci., 44: 49-61.
21. Kodde, D.A. and F.C. Palm, 1986. Wald criteria for jointly testing equality and inequality restrictions. Econometrica, 54: 1243-1248.
22. Ashagidigbi, W.M., S.A. Sulaiman and A. Adesiyan, 2011. Technical and allocative efficiency of poultry egg producers in Nigeria. Agric. J., 6: 124-130.
23. Adeyonu, A.G., A.O. Otunaiya and M.O. Bamiro, 2015. Technical efficiency of poultry egg production in Ibadan Metropolis, Oyo state, Nigeria. Economics, 4: 50-56.
24. Stevenson, R.E., 1980. Likelihood functions for generalized stochastic frontier estimation. J. Econ., 13: 57-66.
25. Coelli, T., D.S.P. Rao and G.E. Battese, 1998. An Introduction to Efficiency and Productivity Analysis. Kluwer Academic Publishers, Boston Dordrecht, London.
26. Nmadu, J.N., I.O. Ogidan and R.A. Omolehin, 2014. Profitability and resource use efficiency of poultry egg production in Abuja, Nigeria. Kasetsart J. Soc. Sci., 35: 134-146.
27. Adedeji, I.A., K.O. Adelalu, S.I. Ogunjimi and A.O. Otekunrin, 2013. Application of stochastic production frontier in the estimation of technical efficiency of poultry egg production in ogbomoso metropolis of oyo state, Nigeria. World J. Agric. Res., 1: 119-123.
28. Adepoju, A.A., 2008. Technical efficiency of egg production in Osun State. Int. J. Agric. Econ. Rural Dev., 1: 7-14.
29. Afolabi, O.I., D.A. Adegbite, O.F. Ashaolu and S.O. Akinbode, 2013. Profitability and resource-use efficiency in poultry egg farming in Ogun State, Nigeria. Afr. J. Bus. Manage., 7: 1536-1540.
30. Ojo, S.O., 2003. Productivity and technical efficiency of poultry egg production in Nigeria. Int. J. Poult. Sci., 2: 459-464.
31. Akinyemi, M., P.A. Okuneye and S.Y. Hosu, 2015. Profit efficiency of poultry egg production system in Ogun State, Nigeria. Sch. J. Bus. Admin., 5: 8-12.
32. Yusuf, S.A. and O. Malomo, 2007. Technical efficiency of poultry egg production in Ogun state: A Data Envelopment Analysis (DEA) approach. Int. J. Poult. Sci., 6: 622-629.
33. Padilla-Fernandez, M.D. and P.L. Nuthall, 2009. Technical efficiency in the production of sugar cane in central Negros area, Philippines: An application of data envelopment analysis. J. Int. Soc. Southeast Asian Agric. Sci., 15: 77-90.