Measurement of Farm Level Efficiency of Beef Cattle Fattening in West Java Province, Indonesia

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Abstract
This study was conducted to identify sources of technical efficiency among beef cattle farmers. This was investigated using the stochastic frontier production function which incorporates a model for the technical efficiency effect. Farm level survey data from 100 beef cattle farmers were obtained using well structured questionnaire. The parameters were estimated simultaneously with those of the model of technical efficiency effects. Asymptotic parameter estimates were evaluated to describe technical efficiency determinants by using the maximum likelihood estimation technique. Result reveal a mean efficiency of 0.77 implying that output from beef cattle fattening could be increased by 23 percent using available technology. Results further reveal that education, experience, number of cattle ownership and credit have significant impact on technical inefficiency. Keywords: technical efficiency, technical inefficiency, beef cattle fattening.

1. Introduction
Beef consumption in Indonesia continues to increase, but the increase was not offset by the addition of adequate production. Population growth of beef cattle is relatively sluggish about 4.23% in 2007 (Direktorat Jenderal Peternakan, 2007). The condition causes low contribution to the nationwide production of beef cattle and resulting in widening gap between demand and supply (Setiyono, et al., 2007). One of the solutions to overcome this gap is increasing domestic beef production. It seems that these efforts will be constrained given that more than 90% of beef production in Indonesia is produced by small farmers with 2-3 cows per household farmers (Priyanti, et al., 2012). The characteristics of small farmers is relatively small-scale businesses and use simple technologies (Azis, 1993), and low productivity (Supadi and Sumedi, 2004). Low productivity leads to lower revenue resulting in weak financial position of farmers to support of economic activities (Nwaru, et al., 2006). Livestock productivity is estimated to 30% influenced by genetic factors and 70% by environmental factors (Prihandini, et al., 2005). Productivity of beef cattle farm are still lower due to various factors including feed, seed and management (Rohaeni, 2006). Managerial ability of farmers associated with the technical efficiency of the farm (Iqbal, et al., 2003). This study estimates the factors influence technical efficiency among beef cattle farmers.

2. Theoretical Framework
Aigner, Lovell and Schmidt (1977) and Meeseun and van den Broeck (1977) in Coelli, et al (1998) proposed the stochastic frontier production function model of the form:

\[ \ln q_i = x_i \beta + v_i - u_i \] (1)

where \( q_i \) represents the output of the \( i \)-th firm; \( x_i \) is a \( K \times 1 \) vector containing the logarithms of inputs; \( \beta \) is a vector of unknown parameters; \( v_i \) is a symmetric random error to account for statistical noise; and \( u_i \) is a non-negative random variable associated with technical inefficiency.

The model defined by (1) is called a stochastic frontier production function because the output values are bounded from above by the stochastic (i.e., random) variable \( \exp(x_i \beta + v_i) \). The random error \( v_i \) can be positive or negative and so the stochastic frontier outputs vary about the deterministic part of the model, \( \exp(x_i \beta) \).

If the technical efficiency of the \( i \)-th activity is defined as the TE \( U_i = \exp(-u_i) \), this technique involves the influence of inefficiency, \( u_i \), which can not be observed. Even if the true value of the parameter vector, \( \beta \), the model of equation (1) is known, the only difference, \( e_i = v_i - u_i \), which can be observed. \( U_i \) is the best predictor for the expected conditional of \( u_i \), given by the value of the \( v_i - u \). This result was first applied by Jondrow, Lovell, and Schmidt Materov (1982) in Coelli, et al., (1998) which produces:

\[ E(u_i | e_i) = -e_i + \sigma_A \left( \frac{\phi(\sigma_A e_i / \sigma_A)}{\phi(\sigma_A e_i / \sigma_A)} \right) \] (2)

where \( \sigma_A = \sqrt{\gamma(1-\gamma)} \); \( e_i = \ln(q_i) - x_i \beta \), and \( \phi(.) \) is the density function of a standard normal random variable.

Battese and Coelli (1988) in Coelli, et al., (1998) states that the best predictor of \( \exp(-u_i) \) is:

\[ E(\exp(u_i) | e_i) = \frac{1 - \phi(\gamma e_i / \sigma_A)}{1 - \phi(\gamma e_i / \sigma_A)} \exp(\gamma e_i + \sigma_A^2 / 2) \] (3)
Much of stochastic frontier analysis is directed towards the prediction of the inefficiency effects. The most common output-oriented measure of technical efficiency is the ratio of observed output to the corresponding stochastic frontier output:

$$TE_i = \frac{q_i}{\exp(z_i^\beta + \delta_i)} = \frac{\exp(x_i^\beta + \xi_i - u_i)}{\exp(x_i^\beta + \xi_i)} = \exp(-u_i)$$

(4)

This measure of technical efficiency takes a value between zero and one. It measures the output of the $i$-th firm relative to the output that could be produced by a fully-efficient firm using the same input vector.

The model proposed by Battese and Coelli (1995) in Coelli, et al., (1998) on the effect of specific technical inefficiency in the stochastic frontier models are assumed independent (but not identical) of non-negative random variable. For the $i$-th activity in the $t$ period, technical inefficiency effect, $u_{it}$, is determined by the distribution of $N(u_{it}, \sigma^2)$, where:

$$\mu_t = z_t\delta$$

(5)

where $z_t$ is a vector ($1xM$) of the explanatory variables are observed, which has a constant value, and $\delta$ is a vector ($Mx1$) of unknown scalar parameters to be estimated.

3. Research Methodology

The study was carried out in Ciamis District as one of the centers of beef cattle production in West Java Province. Data used for this study are mainly primary and were obtain from 100 beef cattle farmers were randomly selected.

The study utilized stochastic production frontier which builds hypothesized efficiency determinants into the inefficiency error components. The model is defined by:

$$\ln Y = \beta_0 + \beta_1\ln X_1 + \beta_2\ln X_2 + \beta_3\ln X_3 + \beta_4\ln X_4 + \beta_5\ln X_5 + \nu_i - u_i$$

(6)

where: $Y$ = body weight gain (kg), $X_1$ = family labor (man-day), $X_2$ = feed forage (kg), $X_3$ = additional feed (cassava) (kg), $X_4$ = feed concentrate (tofu waste) (kg), $X_5$ = veterinary cost (Rp), $\beta$ = coefficient of regression, and $\nu_i$ = random error, $u_i$ = technical inefficiency effects in the model.

In addition to the general model, this inefficiency model was defined to estimate the influence of some farmer’s socio-economic variables on the technical efficiency of the farmers. The model is defined by:

$$\mu_i = \delta_0 + \delta_1Z_1 + \delta_2Z_2 + \delta_3Z_3 + \delta_4Z_4 + \delta_5Z_5 + D$$

(7)

where: $\mu_i$ = technical inefficiency, $Z_1$ = age (years), $Z_2$ = education (years), $Z_3$ = experience (years), $Z_4$ = family size (persons), $Z_5$ = number of cattle ownership (livestock unit), $D$ = credit (dummy, 1 if has an access to credit and 0, otherwise), $\delta$ = regression coefficient.

TE effects model developed by Battese and Coelli (1995) was employed in this study. In this model a Cobb-Douglas type production function and some exogenous factors influencing technical efficiency are determined simultaneously.

4. Results and Discussion

The model specified was estimated by the maximum likelihood method using a Frontier 4.1 software. Result on Table 1 shows ML estimates and inefficiency determinants. The sigma square 0.0051 statistically significant at the 1% level that indicates a good fit and correctness of the specified distribution assumption of the composite error term. The estimated value of the parameter ($\gamma$) in the model of 0.9999 is statistically different from zero at the 1% level. These results indicate a systematic effect that can not be explained by the production function in the form of the dominant sources of stochastic random error. Approximately 99.99% of the variation in the output level of beef cattle fattening attributed to the presence of technical inefficiency in resource use. The generalized likelihood ratio test (107.2903) is statistically significant at the 1% level indicating the present of a one-sided error component. The results of the diagnostic analysis therefore confirm the relevance of stochastic parametric production function and maximum likelihood estimation.

Table 1 shows that family labor and concentrates feed are statistically significant at 5% and 1% levels and have positive signs. Feed forage and veterinary cost are not significant and have positive signs. Additional feed was not significant and has negative sign which indicate over-utilized.

The model employs a log linear equation so the regression coefficient showed the production elasticity of each input. For example, 1% increase in concentrate feed usage will increase production by 0.42%. The sum of all coefficients less than unity (0.61) shows the decreasing returns to scale.

The estimated coefficients of the inefficiency function provide some explanations for the relative technical efficiency levels among the individual farms. Education, experience, number of cattle ownership, and credit had significant effect on the level of technical inefficiency, while age and family size had no significant effect.

The estimate of the parameter for age variable is negative but not significant. This suggests that older farmers are more technically efficient than their younger counterparts are. This result is consistent with the findings by Bamiro, et al., (2006), Alabi and Aruna (2005), and Serin, et al., (2008).
The estimate of education variable is negative and significant at 5% level. This suggests that higher level of education increases technical efficiency. This result is consistent with the findings by Mor and Sharma (2012), Bamiro, et al (2006), Dung, et al (2011), Chang and Villano (2008), Udoh and Etim (2009), Serin, et al (2008), and Oggunyi and Ajibefun (2004). More educated farmers are able to perceive, interpret and respond to new information and adopt improved technologies such as seed and feed much faster than their counterparts.

The coefficient of experience variable is positive and significant at 5% level. This suggests that farmers with more experience achieved lower levels of technical efficiency. This result is consistent with the findings by Bamiro, et al., (2006), Chang and Villano (2008), Haider, et al (2011), Adepoju (2008), Ojo (2003), and Ogunniyi and Ajao (2011).

The coefficient of family size variable is positive but not significant. The results show that farmers with more size of family achieved lower levels of technical efficiency. This result is consistent with the findings by Haider, et al., (2011). Larger family size put extra pressure on the family to work hard for an additional income from off-farm employment thereby reducing technical efficiency.

The estimate of the parameter for number of cattle ownership variable is negative and significant at 1% level. This results show that farmers who raised a higher number of cattle achieved a higher level of technical efficiency. This result is consistent with the findings by Alemdar and Yilmaz (2011) and Mariyono (2006). The higher number of cattle needs more allocation of working time by the farmers thereby reducing technical inefficiency. In addition, farmers will try to improve their knowledge and skills in rearing livestock so that it will achieve a high level of technical efficiency.

The coefficient of credit variable is negative and significant at the 10% level. This suggests that increasing credit use would enhance technical efficiency of sample farms. This result is consistent with the findings by Ayaz and Hussain (2011), Nyagaka, et al., (2010) and Javed, et al., (2012). Access to credit permit farmers to enhance efficiency by overcoming liquidity constraints which may effect their ability to purchase and apply inputs and implement farm management decisions on time hence increasing efficiency.

The differentiation of the technical efficiency level achieved by farmers indicates the differentiation level of mastery and application of technologies. The differentiation of mastery level are caused by education, age, and external factors such as lack of extension (Sukiyono, 2004). Efforts to improve efficiency will be more efficient in terms of cost compared to the introduction of new technologies as a means of increasing agricultural productivity, if farmers are not using efficient technologies (Belbase and Grabowski, 1985; Shapiro, 1983).

5. Conclusion
Estimated farm-specific technical efficiency indices ranged from 0.54 – 0.99 with a mean of 0.77. The average level of technical efficiency suggests that, from a technical standpoint, the opportunity exists to expand beef production using the current level of inputs and the technologies already available in the area. The inefficiency model showed that education, experience, number of cattle ownership, and credit have significant impact on technical inefficiency.

6. Recommendation
Education and experience factors impact on technical efficiency, therefore needed to boost the knowledge and skills of farmers through extension and training activities so farmers can manage the use of production factors efficiently.

7. Acknowledgement
Data were obtained from beef cattle farmers. Hence writers say thank you very much to them in providing data and facilitating the implementation of this study.

References


Appendixes

Table 1. Maximum likelihood estimates and inefficiency functions

<table>
<thead>
<tr>
<th>Variable</th>
<th>Parameter</th>
<th>Coefficient</th>
<th>Standard Error</th>
<th>t-ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Production function</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>$\beta_0$</td>
<td>0.6215</td>
<td>0.2941</td>
<td>2.1133**</td>
</tr>
<tr>
<td>Family labor</td>
<td>$\beta_1$</td>
<td>0.1625</td>
<td>0.0782</td>
<td>2.0774**</td>
</tr>
<tr>
<td>Feed forage</td>
<td>$\beta_2$</td>
<td>0.0520</td>
<td>0.1564</td>
<td>0.3324</td>
</tr>
<tr>
<td>Additional feed</td>
<td>$\beta_3$</td>
<td>-0.0234</td>
<td>0.0362</td>
<td>-0.6453</td>
</tr>
<tr>
<td>Feed concentrate</td>
<td>$\beta_4$</td>
<td>0.4156</td>
<td>0.1486</td>
<td>2.7978***</td>
</tr>
<tr>
<td>Veterinary cost</td>
<td>$\beta_5$</td>
<td>0.0055</td>
<td>0.0261</td>
<td>0.2108</td>
</tr>
</tbody>
</table>

| **Inefficiency function** |           |             |                |         |
| Constant             | $\delta_0$| 0.5108      | 0.2017         | 2.5332***|
| Age                  | $\delta_1$| -0.1040     | 0.1001         | -1.0389 |
| Education            | $\delta_2$| -0.1026     | 0.0614         | -1.6720**|
| Experience           | $\delta_3$| 0.0925      | 0.0482         | 1.9204**|
| Family size          | $\delta_4$| 0.0102      | 0.0464         | 0.2201  |
| Number of cattle ownership | $\delta_5$| -0.7737    | 0.0675         | -11.4681***|
| Credit (dummy)       | $\delta_7$| -0.0353     | 0.0218         | -1.6203*|
| Sigma square         | $\sigma^2$| 0.0051      | 0.0007         | 7.3725***|
| Gamma                | $\gamma$  | 0.9999      | 0.0141         | 71.0769***|

Log likelihood function = 126,7344***

LR Test = 107,2903***

(***) significant at 1%, (**) significant at 5%, (*) significant at 10%

Table 2. Frequency distribution of technical efficiency

<table>
<thead>
<tr>
<th>Efficiency</th>
<th>Frequency</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.51 – 0.60</td>
<td>8</td>
<td>8.00</td>
</tr>
<tr>
<td>0.61 – 0.70</td>
<td>16</td>
<td>16.00</td>
</tr>
<tr>
<td>0.71 – 0.80</td>
<td>33</td>
<td>33.00</td>
</tr>
<tr>
<td>0.81 – 0.90</td>
<td>34</td>
<td>34.00</td>
</tr>
<tr>
<td>0.91 – 1.00</td>
<td>9</td>
<td>9.00</td>
</tr>
</tbody>
</table>

minimum = 0.54; maximum = 0.99, mean = 0.77
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