Rice Farms Efficiency and Factors Affecting the Efficiency in MADA Malaysia

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Abstract: Malaysian rice farming is still constrained by the low productivity despite many supports and subsidies that have been enacted to this sector. The difficulties in improving the yield is potentially caused by the unintensive use of inputs due to the inefficient management on the rice farm. Thus this study aims to measure the rice farm efficiency and factors affecting that efficiency. Two stage analysis was adopted whereas in the first stage data envelopment analysis was used and corrected by the bootstrap method. Then in the second stage a Tobit model was employed to estimate factors affecting the efficiency. On average, the technical efficiency score estimated by DEA was about 0.6375 and implied with a given amount of inputs, the rice farms could increase its output by 57.31%. However, after correcting for the bias, the technical efficiency score was about 0.5366 and indicated that rice farms in MADA could increase its output at 86.35%. Further, by considering the lower and the higher bounds of efficiency scores, on the average, the rice farms could increase its output in the range from 20.13-99.12 with 95% confidence interval. Three factors that significantly affect the rice farm efficiency were the household size, land ownership and secondary level of education of sampled farmers. The positive significant effect of household size implied that farms with more household member was appeared to be more efficiently manage their production. Then, the negative effect of land ownership to the efficiency implied farmers who had the own land were tend to be more efficient than those who rent the land. It was related to their motivation on the production whereas tenant farmers were more motivated to improve their production and get higher income so that they strive to manage the production in a professional manner and receptive to new technology as well. Further, farmers with secondary education level more efficiently managed the rice farm than others because of their passion for managing their production.

Key words: Rice farms, technical efficiency, scale efficiency, bootstrap DEA

INTRODUCTION

Rice is staple and strategic crop in Malaysia. The consumption for rice in 2012 was about 2.1 million t and the production was only able to meet 68.5% of that consumption (Department of Statistics Malaysia, 2011). Despite those strategic function, the increase of rice production triggered by the land expansion is quite difficult currently due to the decreasing of land used for the food crop since the country’s rapid economic development occupies more agricultural area mainly for housing, business and industrial purposes. In 1960, for example, land used by food crops accounted for 31.5% of the total agricultural land in Malaysia, then it has decreased to 16.3% in 2005 (Alam et al., 2010). Further, for two last decades, total number of paddy area is not more than 0.7 million ha with the average growth only about 0.27% year⁻¹.

This fact has prompted the Malaysian authority to consistently increase the rice production by the improvement of the yield through the utilization of the optimal input used, new technology, farm management and provides the incentive for farmers in increasing production such as the paddy price support and the yield increase incentive. For example, government provide various input subsidy schemes which are 240 kg ha⁻¹ mixed fertilizer and 80 kg ha⁻¹ for organic fertilizer as well as RM 200/ha/season subsidy for pesticide control. The price support is currently at RM 248.1 t⁻¹ with the guaranteed minimum price of RM 750 t⁻¹.

Although, there have been many efforts and policies on rice farming, however, there was no significant improvement in the yield. The average yield at 3.9 t ha⁻¹ (Department of Statistics Malaysia, 2011) was not differ from previous studies by Coelli and Battese (1996) that mentioned the actual paddy farm yields in Malaysia vary from 3.5 t ha⁻¹. Comparing to the neighboring countries that yield was lower than Indonesia and Vietnam at 4.9 and 5.5 t ha⁻¹, respectively (FAOSTAT, 2012). Further, rice farms in Malaysia were
characterized as less efficiently managed farms compared to industrial farms since rice farms mainly engaged by small farmers and are not so well-managed. There were 677,884 ha paddy planted which was managed by 300,000 farmers with average farm size about 1.45 ha (Man and Sadiya, 2009).

Those condition conceive that the difficulties in improving the yield is potentially caused by the un-intensive use of input due to the inefficient management on rice farm. Thus, in this context, the measurement of the existing farms efficiency much more useful since it could provide the information about the gap of efficiency performance among the farms and the potential to be improved (Kumbakar and Lovell, 2000). It also shows the possibility to increase the yield without increasing the resource base or developing new technology and it helps determine the under and over utilization of inputs (Padilla-Fernandez and Peter, 2012). Moreover, the analysis of technical efficiency in agricultural sector has been widely used in developing countries due to the importance of productivity growth in order to improve the economic development (Ogundari, 2009). Therefore, this study aims to measure the rice farm efficiency and factors affecting that efficiency.

**METHODOLOGY**

**Data envelopment analysis:** Data Envelopment Analysis (DEA) was formally developed and named by Charnes et al. (1978) where efficiency was defined as the weighted sum of outputs over the weighted sums of input in the constant return to scale assumption. Further, Banker et al. (1984) extended the model to consider the Variable Return to Scale (VRS) assumption and named as the pure technical efficiency. DEA involves the use of linear programming methods to construct a non parametric piece wise surface of frontier over the data. Then, efficiency measure are calculated relative to this surface and this technique identifies the efficient production unit which belong to frontier, otherwise the inefficient ones is remain below the frontier (Coelli et al., 2005). Thus, DEA assumes there are no random effects in the production and does not require the specification of the production function. It just uses a set of inputs that farm want to minimize and a set of output that farms want to maximize. Theoretically, technical efficiency can be examined from an input-orientation or output-orientation. Input oriented technical efficiency means that farms minimize the quantity of inputs while holding output constant and the output oriented technical efficiency means a farm want to maximizes the output given the fixed current quantity of inputs. Two measures provide the same technical efficiency scores when Constant Return to Scale (CRS) technology applied but are unequal when Variable Return to Scale (VRS) was applied.

This study focused on the measure of output oriented technical efficiency due to the main concern on Malaysian rice farming is maximizing the output from a given set of input. Further, we examine the Variable Returns to Scale (VRS) assumption on paddy farm technology since the CRS assumption is more appropriate when all farms are operating at an optimal scale and it is not supported by actual condition on rice farms. The measure on technical efficiency based on the VRS assumption is also named pure technical efficiency since it is free of scale effects (Padilla-Fernandez and Peter, 2012).

By assuming there are n farms which produces a single output using i different inputs and the Variable Returns to Scale (VRS) output oriented DEA model, developed by Charnes et al. (1978) can be expressed as:

$$\max_{\lambda} \phi$$

subject to $\phi x_i + Q \lambda \geq 0$

$y_i - X\lambda \geq 0$

$N^\prime \lambda = 1$

$\lambda \geq 0$  

(1)

where, $1 \leq \phi < \infty$ and $\phi - 1$ is the proportional increase in outputs that could be achieved by the i-farm, with input quantities held constant. Technical efficiency score is defined as $1/\phi$ and varies between zero and one.

It is possible that even though the production units technically efficient but they are not equally productive due to the effects of scale. If the underlying production technology is a globally Constant Return to Scale (CRS), then the production unit is automatically scale efficient. However, when the farms might be too small in its production scale or the production unit are too large and it may operate within the decreasing return to scale, efficiency level might be improved by changing their production scale or the size of operation. Thus, the scale efficiency measurement is one of the important view on paddy farms management.

Scale efficiency is measured as the ratio of technical efficiency on CRS to technical efficiency on VRS. Following Fare et al. (1994), we can define an output orientation measure of scale efficiency at a given input, x and the output, q as follows:

$$SE(x, q) = \frac{d_i(x, q | VRTS)}{d_i(x, q | CRS)} = \frac{TE_{VRTS}}{TE_{CRS}}$$

(2)
**Bootstrap DEA:** The recently advanced DEA estimate is the using of bootstrapping technique which is inspired by the drawback of DEA approach. According to Schmidt (1986), DEA approach did not assume the statistical noise so that all the error term was attributed to inefficiency. Therefore, the efficiency scores generated by DEA were not very robust and highly sensitive to sample selection. Further, Simar and Wilson (2000) mentioned that DEA as the nonparametric approach has been characterized as the deterministic as if to suggest that the method lack any statistical properties.

The bootstrapped DEA was suggested by Simar and Wilson (2000) that derived from some observable data generating process, could remove inherent dependency among efficiency scores and to obtain the bias corrected DEA efficiency scores. The bootstrap is defined as the re-sampling technique as a mean of approximating the properties of the sampling distribution of an estimator when this is difficult to obtain by using alternative means and hence allowing one to construct the confidence interval (Simar and Wilson, 2000).

According to Nastis et al. (2012), the bootstrap method is aimed to analyze the sensitivity of efficiency scores relative to the sampling variations of the estimated frontier and provide the statistical basis for nonparametric efficiency measures. Hence, bootstrapping is the useful way illustrating the sensitivity of DEA efficiency estimates to the variation in sample composition. In particular, the width of the confidence interval for the efficiency of farms located on the fringes of the data set will tend to be quite wide, indicating that the degree to which these estimates are generally based upon rather thin data and hence should be interpreted cautiously. Then, when one has a small sample and a large number of dimension, the confidence interval tend to be wide (Diler, 2011).

**Data:** Data were collected from the survey that conducted at Muda Agricultural Development Authority (MADA), the largest granary areas in Malaysia. Research sample of 150 farmers were drawn using simple random sampling. The data collection used a structured questionnaire on farmer’s production activities including input and output on paddy farm as well as socio-economic characteristics.

In measuring the technical efficiency level of individual farms, one output and five outputs were used whereas the output was defined as the quantity of paddy production for one season (t). Five production inputs included land (ha), seed (kg), fertilizer (kg), pesticide (L), labor (man h). After detecting the outlier, from 150 samples, we dropped eight extreme observations as the outliers in order to reduce the possibility of DEA estimates sensitivity to those outliers. Then efficiency scores were recalculated using the final sample of 142 farms.

**EMPIRICAL RESULTS**

**Technical efficiency estimate:** The summary of statistics for variables gathered from the survey are reported in Table 1. The average paddy production of the sampled farms was 2.37 t with the minimum production at 1.05 t and maximum production at 5.42 t. Standard deviation of the production was quite high (77.38) which indicated the large variability on paddy production among the sampled farms.

On average, the seed used on paddy farms was about 68 kg and there were some farms used it until 113 kg. Yet, the variability of used seed among the sampled farms was not large since the standard deviation for seed was lower than for other inputs. The large variability on input used among farms was found on the utilization of fertilizer which was 83.79 and indicated that many farms did not comply with a good farm practice especially in the utilization of the fertilizer.

The result of VRS or pure technical efficiency, its bootstrapping methods and the scale efficiency are presented in Table 2. On the average, the bias corrected TE scores were significantly lower than the VRS TE scores and similar result have been reached by Linh (2012) for rice farming in Vietnam. The technical efficiency score

<table>
<thead>
<tr>
<th>Variables</th>
<th>Average</th>
<th>Minimum</th>
<th>Maximum</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Production (kg)</td>
<td>2353.750</td>
<td>1054.850</td>
<td>5421.680</td>
<td>77.382</td>
</tr>
<tr>
<td>Land (ha)</td>
<td>4.250</td>
<td>1.028</td>
<td>9.536</td>
<td>2.137</td>
</tr>
<tr>
<td>Seed (kg)</td>
<td>68.045</td>
<td>15.060</td>
<td>113.680</td>
<td>18.054</td>
</tr>
<tr>
<td>Fertilizer (kg)</td>
<td>351.975</td>
<td>237.590</td>
<td>659.920</td>
<td>83.795</td>
</tr>
<tr>
<td>Pesticide (L)</td>
<td>1.896</td>
<td>1.000</td>
<td>8.180</td>
<td>3.187</td>
</tr>
<tr>
<td>Labor (man h)</td>
<td>25.653</td>
<td>5.269</td>
<td>51.969</td>
<td>17.725</td>
</tr>
</tbody>
</table>

Table 2: Technical and scale efficiency score estimated by DEA and bootstrap methods

<table>
<thead>
<tr>
<th>Description</th>
<th>VRS/pure TE</th>
<th>Bias corrected TE</th>
<th>Lower bound</th>
<th>Upper bound</th>
<th>Scale efficiency</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average</td>
<td>0.6357</td>
<td>0.5866</td>
<td>0.5022</td>
<td>0.8374</td>
<td>0.8576</td>
</tr>
<tr>
<td>Median</td>
<td>0.6349</td>
<td>0.5714</td>
<td>0.5426</td>
<td>0.7852</td>
<td>0.9107</td>
</tr>
<tr>
<td>Minimum</td>
<td>0.1570</td>
<td>0.0711</td>
<td>0.0489</td>
<td>0.1690</td>
<td>0.1999</td>
</tr>
<tr>
<td>Maximum</td>
<td>1.0000</td>
<td>0.8971</td>
<td>0.9417</td>
<td>0.9877</td>
<td>1.0000</td>
</tr>
<tr>
<td>SD</td>
<td>0.3243</td>
<td>0.3589</td>
<td>0.2284</td>
<td>0.2018</td>
<td>0.3229</td>
</tr>
</tbody>
</table>
estimated by DEA was about 0.6375 and means that with a
given amount of inputs, on average, the rice farms could
increase its output by 57.31%. This result was consistent with Thiam et al. (2001) on his study about
technical efficiency in developing country agriculture,
Nargis and Lee (2013) in the study on efficiency analysis
of boro rice production in north central region of
Bangladesh and Padilla-Fernandez and Peter (2012) with
study about farm size and its effect on productive
efficiency of sugar cane farm in Central Negros, Philippines.

However, after correcting for the bias, the technical efficiency score was 0.5366 and indicated that rice farms
in MADA still could increase its output by 86.35% on the
same level of inputs. This bias corrected TE score obtained from the bootstrap methods was more robust
than the VRS TE estimated by DEA due to its adjustment
to the sample variation. Further, by considering the lower
and the higher bounds, on the average, the rice farms
could increase its output in the range from 20.13-99.12%
with 95% confidence interval. This confidence interval
was rather wide due to the small sample in this analysis.

Further, the scale efficiency of rice farms was about
0.8576. It implied that essentially the average farms were
very close to optimal scale since only 14.24% additional
productivity gain was feasible to reach the optimal scale
by assuming no other constraining factors. The lower
VRS technical efficiency scores compared to the scale
efficiency scores suggested that inefficiencies were
mostly due to inefficient management or inefficient
technical practices rather than the scale of production or
the size of operation. This result is consistent with study
by Padilla-Fernandez and Peter (2012), Yusuf and Malomo

Table 3 shows the distribution of the paddy farm and
separated on two categories. According to the VRS
technical efficiency, the best practice farms with the TE
score above 0.90 were about 13.4% and it was higher than
those on the bias corrected TE (5.63%). Conversely,
based on the bias corrected TE, there were 3 farms (2.11%) which were not efficiently managed the rice production
and those farms were not founded on the VRS TE. These
difference potentially caused by the sensitivity of VRS TE
to the sample variation.

The comparison of farms distribution on both
categories can be expressed clearly as well by dividing
those farms into below or above the average technical
efficiency scores (0.63). On the VRS/pure technical
efficiency categories, there were 46.5% paddy farms with
the efficiency score above the average. Yet, on the bias
corrected TE category, there were less farms (35.2%) with
the efficiency score above the average value. Hence,
according to the corrected bias TE, mostly paddy farms
(59.2%) were not efficient due to its scores still below the
average value.

**Factor affecting the efficiency:** Regarding the previous
discussion that inefficiencies on sampled rice farms were
mostly due to the inefficient management rather than the
scale of operation, we attempt to examine factors affecting
the efficiency by following the two step approach as
suggested by Coelli and Battese (1996). Factors that
supposed to be related to the management on rice
production were included on the analysis. As we know, a
common practice in the DEA literature for estimating the
factors affecting the efficiency had employed the Tobit
model regression since the efficiency scores as the
dependent variables had the range from 0-1 (Sharma et al.,
1999).

We regressed the estimated efficiency scores
obtained from first step as a function of
explanatory variables which were socio-demographics
variables, ownership and access to credit. Those
socio-demographics variables were the farmers’ age,
household size, the main job (whether the full time farmer),
education and involvement on the extension activities.
Two special variables were the land ownership and access
to credit were included in the model in order to estimate
the role of those variables to the rice farm efficiency. The
following was the Tobit model used in this study:

$$Q_i = \beta_0 + \beta_1 \text{Age}_i + \beta_2 \text{HHSize}_i + \beta_3 \text{Job}_i + \beta_4 \text{Ext}_i + \beta_5 \text{LandOwn}_i + \beta_6 \text{Credit}_i + \beta_7 \text{Noed}_i + \beta_8 \text{Primary}_i + \beta_9 \text{Secondary}_i + \beta_{10} \text{HigheDuc}_i + e_i$$

The variable of age was defined as the household
head’s age and the household size was the total number
of household members. Other variables that might affect
the technical efficiency were expressed as the
binary/dummy variables. The dummy variables of job was
divided into one if the paddy farmer as the main job and
zero for others. The involvement on extension services
was defined as one and zero for otherwise.
Table 4: Factors affecting the rice farm efficiency

<table>
<thead>
<tr>
<th>Variables</th>
<th>Parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total No. of observation</td>
<td>142,000</td>
</tr>
<tr>
<td>Loglikelihood</td>
<td>17.7320</td>
</tr>
<tr>
<td>Sigma</td>
<td>0.2374 (16.85)***</td>
</tr>
<tr>
<td>Farmer's age</td>
<td>-0.0020 (1.08)</td>
</tr>
<tr>
<td>Household size</td>
<td>0.0193 (2.08)***</td>
</tr>
<tr>
<td>Main job</td>
<td>0.0198 (0.34)</td>
</tr>
<tr>
<td>Involvement on extension services</td>
<td>-0.0119 (0.33)</td>
</tr>
<tr>
<td>Land ownership</td>
<td>-0.073 (1.91)**</td>
</tr>
<tr>
<td>Access to credit</td>
<td>0.0221 (0.60)</td>
</tr>
<tr>
<td>No education</td>
<td>0.2214 (0.93)</td>
</tr>
<tr>
<td>Primary</td>
<td>0.1987 (0.88)</td>
</tr>
<tr>
<td>Secondary</td>
<td>0.2661 (1.17)**</td>
</tr>
<tr>
<td>High education</td>
<td>0.0334 (0.11)</td>
</tr>
</tbody>
</table>

Values in parentheses are t-statistics. ***, *** significantly at 5% and 1%, respectively.

Land ownership was another dummy variable which one for the farmers who have their own land and zero for others who rent the land. Further, access to credit that often characterized as the farms capability criteria to improve their production also expressed as dummy whereas one for farms that have the access and zero for otherwise. Household head's education was divided into four categories: No formal education, primary school (from 1-6 years), secondary school (from 7-12 years) and high education (12 years and up).

The result in Table 4 shows that the model appears to fit data well due to the positive sigma coefficient and statistically significant at 1% level. Out of ten variables included in the model, household size, land ownership and secondary level of education provide the most significant effect to the rice farms efficiency. The positive significant effect of household size implied that farms with more household member was appeared to be more efficiently manage their production since many worker that potentially involved in the production.

Land ownership also had the significant effect to the rice farm efficiency but on the negative direction. It implied farmers who own the land were tend to be more inefficient than those who rent the land. It was related to the motivation on production whereas tenant farmers were more motivated to improve their production and get higher income so that they strive to manage the production in a professional manner and receptive to new technology as well. Further, from four categories of farmer’s education, farmers with secondary education level more efficiently managed the paddy farm than others because of their passion for managing the rice farm. Other factors such as age, job, involvement on extension service, access to credit were not significant in affecting the rice farm efficiency.

CONCLUSION

The findings of this study show that on average, the bias corrected TE scores (0.5366) were significantly lower than the variable return to scale TE scores estimated by DEA (0.6375). Efficiency score estimated by DEA at 0.6375 means that with a given amount of inputs, rice farms could increase its output by 57.31%. However, after correcting for the bias, the technical efficiency score was about 0.5366 and indicated that rice farms in MADA could still increase its output by 86.35%. By considering the lower and the higher bounds of efficiency scores, on the average, the rice farms could increase its output in the range from 20.13-99.12% with 95% confidence interval.

The scale efficiency of rice farms at 0.8576 implied that essentially the average farms were very close to optimal scale. The interesting condition can be seen on the lower VRS technical efficiency scores compared to the scale efficiency scores because it suggested that inefficiencies were mostly due to inefficient management. Therefore, the analysis on factors affecting the efficiency is supposed to conducted by applying the Tobit regression model.

Three factors that significantly affect the rice farm efficiency were household size, land ownership and secondary level of education of sampled farmers. The positive significant effect of household size implied that farms with more household member was appeared to be more efficiently manage their production. Then, the negative effect of land ownership implied farmers who had the own land were tend to be more inefficient than those who rent the land. It was related to the motivation on production whereas tenant farmers were more motivated to improve their production and get higher income so that they strive to manage the production in a professional manner and receptive to new technology as well. Further, farmers with secondary education level more efficiently managed the paddy farm than others because of their passion for managing the rice farm.

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