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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 inefficient 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 strived 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 insentive for farmers in increasing production such as the paddy price support and the yield increase insentive. 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 guaranted 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

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characterized as less efficiently managed farms compared to industrial farms since rice farms mainly enganged 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 unintensive 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 (Kumbhakar and Lovell, 2000). It also shows the possibility to increase the yield without increasing the resourse 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 liner programming methods to construct a non parametric piece wise surface of frontir 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 orientated technical efficiency means that farms minimize the quantity of inputs while holding output constant and the output orientated 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 orientated 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 ouput 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:

$$\begin{gathered} \max_{\phi\lambda}\phi \\ \text{subject to } -\phi qi+Q\lambda\geq 0 \\ xi-X\lambda\geq 0 \\ N1'\lambda = 1 \\ \lambda\geq 0 \end{gathered} \tag{1}$$

where, $1\leq\phi<\infty$ and ϕ-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 eventhough 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 orientated measure of scale efficiency at a given input, x and the output, q as follows:

$$SE(x, q) = \frac{d_i(x, q\,|\,VRTS)}{d_i(x, q\,|\,CRTS)} = \frac{TE_{CRTS}}{TE_{VRTS}} \tag{2}$$

Bootstrap DEA: The recently advance on 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 bootstraped DEA was suggested by Simar and Wilson (2000) that derived from some unobservable 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 relatives 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 outler, 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 1: Summary statistics of variables used on the study

Variables	Average	Minimum	Maximum	SD
Production (kg)	2373.790	1054.850	5421.680	77.382
Land (ha)	4.250	1.028	9.530	2.137
Seed (kg)	68.045	15.060	113.680	18.054
Fertilizer (kg)	351.975	237.590	659.920	83.795
Pesticide (L)	1.896	1.000	8.180	1.387
Labor (man h)	25.653	5.260	51.969	17.725

SD: Standard deviation

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

Description	VRS/pure TE	Bias corrected TE	Lower bound	Upper bound	Scale efficiency
Average	0.6357	0.5366	0.5022	0.8324	0.8576
Median	0.6349	0.5714	0.5426	0.7752	0.9107
Minimum	0.1570	0.0711	0.1489	0.1690	0.1999
Maximum	1.0000	0.8971	0.9417	0.9877	1.0000
SD	0.3243	0.3589	0.2234	0.2018	0.3229

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%. These 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 Negos, Phillipines.

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 (2007) and Rios and Shively (2005).

Table 3 shows the distribution of the paddy farm and seperated 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.

Table 3: Distribution of initial and corrected technical efficiencies

	VRS/pure TE		Bias corrected TE	
Efficiency score	No. of farms	%	No. of farms	%
0.00-0.09	0	0.0	3	2.11
0.10-0.19	3	2.1	10	7.04
0.20-0.29	15	10.6	17	11.97
0.30-0.39	5	3.5	13	9.15
0.40-0.49	13	9.2	19	13.38
0.50-0.59	21	14.8	22	15.49
0.60-0.69	30	21.1	23	16.20
0.70-0.79	18	12.7	18	12.68
0.80-0.89	18	12.7	9	6.34
0.90-1.00	19	13.4	8	5.63

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 inluded 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:

$$\varnothing_i = \beta_0 + \beta_1\ Age_i + \beta_2\ HHSize_i + \beta_3\ Job_i + \beta_4\ Ext_i + \beta_5\ LandOwn_i + \beta_6\ Credit_i + \beta_7\ Noedu_i + \beta_8\ Primary_i + \beta_9\ Secondary_i + \beta_{10}\ Highedu_i + \varepsilon_i$$

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 efficieny 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

Variables	Parameters
Total No. of observation	142.0000
Loglikelihood	17.7320
Sigma	0.2374 (16.85)***
Farmer's age	-0.0020 (-0.98)
Household size	0.0193 (2.08)***
Main job	0.0198 (0.34)
Involvement on extension services	-0.0119 (-0.31)
Land ownership	-0.0737 (-1.91)**
Access to credit	0.0241 (0.6)
No education	0.2214 (0.93)
Primary	0.1987 (0.88)
Secondary	0.2661 (1.17)**
High education	0.0334 (0.11)

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

Land ownership was another dummy variable which one for the farmers who has 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 yeras 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 the 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 strived 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, acces 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 strived 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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