Comparison of Technical Efficiency of Rice Mill Systems between Thailand and Taiwan

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Abstract

This study attempts to measure the technical efficiency and to find the sources of inefficiency of rice mill businesses in Thailand and Taiwan. The survey was based on cross-sectional data in 2000. Purposive sampling technique was applied to select 36 commercial rice mills in Thailand and 35 in Taiwan. Data Envelopment Analysis (DEA) was used to estimate technical efficiency level. The results showed that total technical efficiency and pure technical efficiency of rice mills in Thailand on the average are less than Taiwan. However, the appropriate scale efficiencies of rice mills in both countries are almost identical. For the sources of inefficiency, it was found that the only variable that affected the technical efficiency was capacity in Thailand. The other variables were not significant for both Thailand and Taiwan.

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1. Introduction

Rice is a significant commodity for both Thailand and Taiwan's economies as export and staple food; and by-products of rice are also important for human and animal consumption. For the 1999/2000 crop year, Thailand planted about 64.4 million *rais* to produce 24.2 million tons of paddy, yielding roughly 16.5 millions tons of milled rice. Of this, approximately 9.7 million tons were used for domestic consumption and about 6.8 million tons were left available for export. (Office of Agricultural Economics, 2001).

The annual rice production in Taiwan was increasing during the early postwar years. It increased steadily from 1.2 million tons in 1964 to 3.4 million tons in 1976. However, since 1977 it had declined sharply to 1.9 million tons in 1999 (Taiwan Food Statistics Book, 2000). Hence, the area harvested for rice production was decreasing from 3.4 million *rais* in 1946 to 2.2 million *rais* in 1999. More than 90% of rice in Taiwan is used for food, feed, seed, processing and brewing (Lee, 1996).

A rice mill is an intermediate entity playing two important roles. As a production unit, it converts paddy into milled rice; and, as a marketing unit, it purchases paddy from farmers and forms part of the total distributive chain of milled rice to consumers, commercial merchants and government agencies. This inevitably has led to the existence of many rice mills with a variety of size and technology in almost every region of these two countries. Rice mill businesses are highly competitive in the rice marketing system. Taiwan is seen to be the leading country in this industry given its highly efficient production. This high efficiency was primarily due to the use of high processing technology. Recently, large mills in Thailand are beginning to modify machines for labor saving, like the assembly line, dumpcart, etc.

So far, it remains unknown how this capital intensive technology has contributed to improving the efficiency of production in the rice mill industry of Thailand. It is noticeable that the technology might not be appropriate for the labor available in Thailand. Most rice mills in Thailand are still using a lot of labor force for bagging, piling, carrying, loading, etc. On the other hand, given the same production techniques and scale, the firms may operate with different efficiencies. In addition, efficiency is also due to the differences in firm's availability of non-measurable inputs, such as managerial ability, which affect the efficiency of measurable combined inputs such as the quantities of paddy and labor.

Therefore, it is important that a study be conducted to compare the technical efficiencies, and investigate how efficiently the resources are being utilized in the production management process in the rice milling industry (of the two countries) in order to produce the potential output.

This paper is organized into five sections. Following this introduction, technical efficiency and DEA are introduced and explained. In section 3 the data collection used in the study are described. Next, the various model specifications employed in the empirical analysis are presented. The last two sections cover the empirical results of this study and a summary of the findings.

2. Technical efficiency and DEA

The conventional definitions of efficiency used in economics literature can be traced back to Farrell (1957). Farrell introduced a simple method of measuring the efficiency of firm directly from observed data, in a single output taking into account multiple inputs. The efficiency consisted of both technical efficiency and allocative efficiency. The measure of technical efficiency that Farrell introduced is an input orientated, measured by how much inputs could be reduced whilst maintaining the existing level of output (Fraser and Cordina, 1999).

Data Envelopment Analysis (DEA) is a non-parametric mathematical programming methodology based upon the work of Farrell. It involves the use of linear programming to construct an efficiency frontier that provides a means by which all firms can be assessed in terms of relative efficiency. DEA approach has two main advantages in estimating efficiency scores. First, it does not require the assumption of a functional form to specify the relationship between inputs and outputs. Second, it does not require the distributional assumption of the inefficiency term.

The constant returns to scale (CRS) assumption means that average productivity, denoted by output/ input ratio is not dependent on scale of production. However, the most general assumption that can be made in respect of returns to scale is that they are variable. This permits constant but also increasing and decreasing returns to scale for different scale sizes. To allow for this possibility, variable returns to scale (VRS) that measure technical efficiency can be decomposed into pure technical efficiency and scale efficiency (SE). The VRS rating is obtained when control for the scale size of the Decision Making Unit (DMU) and SE measures the impact of scale size on the productivity of a DMU. That the technical efficiency score (in both CRS and VRS models) equals one implies full efficiency; on the other hand, if the score is less than one it indicates technical inefficiency. Similarly for SE, if the score equals one then there is scale efficiency or if the score is less than one there is scale inefficiency.

Consider the situation with n firms or decision-making units (DMUs), each producing a single output by using m different inputs. Here, Y_i is the output produced and X_i is the (m×1) vector of inputs used by the *i*th DMU. Y is the (1×n) vector of outputs and X is the (m×n) matrix of inputs of all n DMUs in the sample.

The technical efficiency (TE) measure under constant returns to scale (CRS) is obtained by solving the following DEA model:

$$\begin{aligned} &\min_{\theta_i^{CRS},\lambda} \theta_i^{CRS} \\ \text{Subject to} \quad & Y_i \leq Y\lambda \\ & \theta_i^{CRS} X_i \geq X\lambda \\ & \lambda \geq 0 \end{aligned} \qquad (1)$$

where θ^{CRS} is a TE measure of the *i*th DMU under CRS and λ is an n×1 vector of weights attached to each of the efficient DMUs. A separate linear programming (LP) problem is solved to obtain the TE score for each of the n DMUs in the sample.

If θ^{CRS} = 1, the DMU is on the frontier and is technically efficient under CRS. If $\theta^{CRS} < 1$, then the DMU lies below the frontier and is technically inefficient.

The CRS or 'overall' (TE_{CRS}) measure can be decomposed into its 'pure' TE and scale efficiency components by solving a variable returns to scale (VRS) DEA model, which is obtained by imposing additional constraint on equation (1) (Banker et al., 1984) as specified below.

$$\min_{\theta_i^{VRS},\lambda} \theta_i^{VRS} \tag{2}$$

Subject to

$$Y_i \leq Y\lambda$$

$$\theta_i^{VRS} X_i \geq X\lambda$$

$$\sum_{j=1}^{n} \lambda_j = 1$$

$$\lambda \geq 0$$

Let θ_i^{VRS} denote the TE index of the *i*th DMU under variable returns to scale (TE_{VRS}).

Because the VRS analysis is more flexible and envelops the data in a tighter way than the CRS analysis, the VRS TE measure (θ^{VRS}) is equal or greater than the CRS measure (θ^{CRS}). This relationship is used to obtain a measure of scale efficiency (SE) of the *i*th DMU as

$$SE_i = \frac{\theta_i^{CRS}}{\theta_i^{VRS}} \tag{3}$$

where SE = 1 indicates scale efficiency or CRS and SE < 1 indicates scale inefficiency.

The second stage, regression can be used to explain the efficiency scores for the various firm-specific factors as to identify the factor affecting technical inefficiency from the DEA results.. This analysis can be helpful in targeting extension activities to deal with technical inefficiencies in production. Tobit regression was used to identify possible factors associated with inefficiency.

When dependent variables are discrete, there are other estimation techniques, which provide maximum likelihood estimates such as Logit, Probit and Tobit. In case of Logit and Probit, the dependent variable can take any value between 0 or 1 but in the case of Tobit the dependent variable can take any value between 0 and any arbitrary numbers. So, for this study the most suitable method is Tobit because inefficiency in percentage which is a dependent variable that lies between 0 and 100 (Llewelyn and William, 1996; Burki and Terrell, 1998; Thiam et. al., 2001).

3. Data collection

Stratified and purposive sampling techniques were used to select the rice mills based on cross sectional data in 2000. The rice mills to be chosen as representatives of the rice mill industry of Thailand are in the Northeastern, Central and Northern regions as rice planted-area. Surin, Phitsanulok and Chiang Mai provinces were selected to represent these areas respectively. Eleven observations were chosen from the name list of the Provincial Commercial Office, which classified commercial mills in medium and large-scale businesses. In addition, one cooperative with a rice mill firm in each province was chosen for comparison with private rice mills.

There are more than 1,300 rice mills in Taiwan. However, most of them are located in the Central and Southwestern regions, as they constitute the largest proportion of rice growing area in the country. Therefore, rice mills in the two regions were selected for the study. However, the observations to be covered by the study were drawn only from the 135 rice mills that have been registered as members of Taiwan Rice and Cereals Industry Association. The 30 observations are selected as representative of private rice mill. Moreover, five farmer associations were chosen to compare with private rice mill operation.

4. Model specification

The procedures are two-dimensional in order to carry the purpose of this study. Data Envelopment Analysis (DEA), the analytical method, was employed to analyze and compare the level of technical efficiency for rice millers by combining all rice mills in both Thailand and Taiwan. An input oriented measure, output is aggregated into one category and inputs are aggregated into four categories, namely, paddy, land, labor, and value of machine, as variables included in the model specification in equations 1 to 3 in section two. The variables are adjusted to account for such exchange rate differences between Thailand and Taiwan. These output and input variables are described below.

Output (Y) represents the total quantity of rice after processing (ton).

Paddy (X_1) represents the total quantity of annual paddy (ton).

Land (X_2) represents the total quantity of land (*rai*).

Labor (X_3) represents the total amount of family labor and hired labor (person).

Machine (X_4) represents the initial value of machine in mill operation (*baht*).

The survey data was given that rice processing was the dominant activity of the sample firms. Therefore, the output is total quantity of head rice produced by individual rice mill. The various inputs used in the analysis were adjusted. Paddy is only one raw material of processing. It was measured by ton per year of total quantity paddy used in 2000. Next, land was the total number of *rai* that the rice mill possessed as their processing area, warehouse and rice mill yard. Labor input was measured in number of persons. Each person was defined as one man working 8 hours a day in the rice processing activity. Labor was measured by skilled and unskilled labors. Most rice mills are the family businesses; family labor ranging at 2-5 people per mill was assumed to be skilled labor. Except for hired managers, hired labor was unskilled labor to perform bagging, piling, carrying, and loading for example. Hence, disparity of labor was the quantity of hired labor. Finally, capital investment used for rice mill includes fixed cost and variable cost. Paddy is one variable that can be indicated in the variable cost. This study used value of machine to represent capital.

The variation of technical efficiencies in the rice mill industry is caused by two major reasons. One is the variation in technical aspect with respect to the quality of milling machine i.e. machine capacity and source of power used. The other is the variation in other factors such as managerial skill, labor skill, type of business, etc.

Firm specific estimates of pure technical efficiency are used as a dependent variable. Technical efficiency scores are regressed on the explanatory variables which include years of establishment, degree to full capacity of operation, experience. Number of years in school are used for education of entrepreneurs. Dummy variables are used for energy source in operation and business type (i.e. private rice mill and cooperatives rice mill) of each rice mill.

The Tobit regression to estimate an equation of the general form is

$$\text{PTE}_\text{i} = \alpha + \beta_1 Year_i + \beta_2 Capa_i + \beta_3 Exp_i + \beta_4 Edu_i + \beta_5 Energy_i + \beta_6 Type_i + \varepsilon_\text{i} \qquad (4)$$

Where:

PTE_i = Pure Technical Efficiency score for rice mill i

$Year_i$ = Number of years established of rice mill

$Capa_i$ = Maximum degree to full capacity of machine operating (ton per day)

Exp_i = Manager's experience (Number of years to engage in rice mill business)

Edu_i = Education of entrepreneurs (number of years in school)

$Energy_i$ = 1 if from new technology
= 0 otherwise

$Type_i$ = 1 if rice mill if private
= 0 otherwise (association or cooperative)

α, β = parameters.

ε_i = Error term.

5. Empirical findings

When combining rice mills in Thailand and Taiwan, wide variations were found in both the input used as paddy and expenditure on machine and rice output data (Table 1). That is, there are large variations in the levels at which inputs were being used. Also note that the initial values of machine and paddy have a much larger proportionate variation maximum/minimum than those of land and labor. This may be a reflection of the increased capital intensification and automation in the rice mill industry. In addition, this shows that the size of Taiwan's rice mill is more uniform, and less land but higher investment is used.

Table 1 Descriptive statistics for the combined samples of 71 rice mills in Thailand and Taiwan

Input/output variables	Minimum	Maximum	Mean	Standard Deviation
Output				
Rice (ton)	585*	112,320*	8,853.87	14917.14
Inputs				
Paddy (ton)	900*	172,800*	14,101.93	23422.28
Land (*rai*)	0.45	40*	11.86	16.60
Labor (people)	4*	67*	18.83	14.75
Machine (baht)	320,000*	79,500,000	12,364,000	12,336,879.98

Note: * = extreme original from Thai rice mills.

Source: Survey.

5.1. DEA results

The results are summarized by the frequency in Table 2. The mean of total technical efficiency and pure technical efficiency of rice mills in Thailand is less than that of Taiwan. The average CRS measures of technical efficiency for rice mills in the samples for Thailand and Taiwan are 0.84 or 84 % and 0.87 or 87 %, respectively. While, the average VRS measures are 0.87 or 87 % in Thailand compared with 0.91 or 91 % in Taiwan.

The first thing to note about these results is that, under the CRS measure of technical efficiency 8.3 % of the sample rice mills in Thailand (3 out of 36 mills) and 11.4 % (4 out of 35 mills) of rice mills sample in Taiwan are identified as technically efficient, i.e. operating at best practice.

Table 2 Comparison of technical efficiency score of rice mills in Thailand and Taiwan

Range of efficiency score	Number of mills					
	CRS		VRS		SE	
	Thailand	Taiwan	Thailand	Taiwan	Thailand	Taiwan
Equal to 100%	3	4	7	11	4	4
>90 - < 100%	9	8	9	8	21	20
80 - < 90%	11	20	12	13	8	6
70 - <80%	11	1	6	1	3	4
60 - < 70%	2	2	2	2	0	1
Mean efficiency	0.841	0.871	0.874	0.910	0.963	0.958
Minimum efficiency	0.635	0.625	0.640	0.674	0.870	0.832
Maximum efficiency	1.00	1.00	1.00	1.00	1.00	1.00

Note: total number of observations = 71 mills including 36 mills in Thailand and 35 mills in Taiwan

Source: Calculation.

The average levels of technical inefficiency in Thailand and Taiwan are 0.16 or 16 % and 0.13 or 13 %, respectively (Table 2). This implies that, by adopting best practices, rice mills can, on average, reduce their inputs combination of land, labor, paddy, and expenditure on machine, by at least 16 % in Thailand and 13 % in Taiwan. However, to decrease the raw material of paddy in some cases could not be done, since the study analyzed the combined data in both countries and the higher percentage of head rice after processing in Taiwan has influence to enhance technical efficiency than in the case of Thai rice mills. The potential reduction in inputs from adopting best practices varies from mill to mill. The best practice or frontier firms cannot reduce their inputs. However the other 91.7% of rice mills in Thailand and 88.6% of rice mills in Taiwan can reduce their inputs according to the DEA results. They can do this by forming benchmarking partnerships with relevant best-practice firms and emulating the best practices of the latter.

The total technical efficiency can be decomposed into pure technical efficiency and scale efficiency. The VRS measure of technical efficiency of 19.4 % and 31.4 % (of the sample of rice mills in Thailand and Taiwan) are identified as technically efficient and operating at best practice. The average VRS measure of technical efficiency for mills in Thailand is 0.87 and 0.91 in Taiwan (Table 2). This means that 3 % and 4% of the difference between VRS technical inefficiency and CRS technical inefficiency identified above are due to rice mills operating at non-optimal scale.

As indicated earlier, the scale efficiency of the rice mills can be measured by the ratio of the constant returns to scale and the variable returns to scale input measures of technical efficiency. A ratio of unity implies that the rice mill is operating at optimal scale. A ratio of below unity implies that the rice mill is experiencing technical inefficiency because it is not operating at its optimal scale.

When technical efficiencies obtained with CRS and VRS models are equal then the operator is running under constant returns to scale (Coelli *et al.*, 1998). The results for scale efficiency suggested that 11.1 and 11.4 % of the rice mills in Thailand and Taiwan are operating at their own optimal scale (constant returns to scale). Rice mill scale efficiency in Thailand is a little higher about 96.3 % than 95.8% in Taiwan; hence, inefficiency due to scale accounts for approximately 4 percentage points of the average technical inefficiency of 16 and 13 % in Thailand and Taiwan. According to the results, therefore, over 80 % of the rice mills in the samples are experiencing some technical inefficiency due to their size.

5.2 Use of DEA results to study inefficiency in individual rice mill

Throughout the DEA modeling approach for efficiency analysis, it is possible to achieve two types of results. First, it is possible to identify the adjustments that can be made in the use of inputs in inefficient mills by comparing them with their ‘peer’ mills. Second, the factors that can be manipulated to minimize the excessive use of inputs and hence reduce the costs of production can be established.

For example, by using the result of the VRS DEA model to work out what is required by inefficient rice mills to become efficient. Taking the rice mill Decision Making Unit (DMU) 1, with efficiency scores of 0.804 and 0.832 under the CRS and VRS assumptions, respectively. For rice mill, the firms 19 (lambda weight = 0.020), 41 ((lambda weight = 0.159) and 65 ((lambda weight = 0.820) are referents when VRS are assumed.

The production practices of the DMU-1 and its referents are compared in Table 3. The use of input by the DMU-1 is excessive. The above comparison would suggest strategies for the DMU-1 to rationalize the use of its inputs. The lambda values obtained from the DEA solution for this rice mill provide a composite DMU, which would produce the equivalent level of output, however by using lesser levels of input.

A composite DMU result shows that DMU-1 should reduce land and labor to 1.4 *rai* and approximately 12 men, respectively. In addition, rice mill should increase their machine utility such as expand time in operation, to raise technical efficiency. Nevertheless, paddy could not be decreased from 12,480 tons to 10,388.4 tons as it is restricted by the cracking percentage of milled rice in Thailand.

Table 3 Input use levels of the DMU-1 and its referent DMUs in the VRS case

Variable in DEA model	**Input used level**	**Input level of the referent units**			**Composite DMU**
	DMU-1	DMU-19	DMU-41	DMU-65	
Lambda values		0.020	0.159	0.820	
Output					
Rice (ton)	7,488	36,000	25,900	3,200	7,488
Inputs					
Paddy (ton)	12,480	60,000	36,909	4,000	10388.4
Land (*rai*)	14	33	1.35	0.62	1.4
Labor (people)	26	28	22	8	11.2
Machine (bath)	10,000,000	10,000,000	29,688,000	4,128,000	8,324,059.8

Source: Calculation.

The results found in this section are the difference in technical efficiency that exists among rice mills in Thailand and Taiwan in different categories. The interesting issue to investigate is, "what are the factors that influence the difference in technical efficiency level?" The next section is presented with the purpose of answering this question.

5.3 Factors affecting technical inefficiency in rice mill industry

To assess the sources of measured efficiencies, this study uses a Tobit regression model as efficiency scores are truncated (Zheng et al., 1998). Therefore, firm specific estimates of pure efficiency are used as a dependent variable and as information on potential explanatory variables defined in section 4.

The estimation used the Tobit procedure in the EVIEW 4.1 software package. The outcomes are presented in Table 4. Technical efficiency measures are regressed on number of years established, degree to full capacity of operation, experience, education level of entrepreneurs, energy source in mill operation and dummy variable of business type (i.e. private rice mill and cooperatives rice mill) of each rice mill.

Surprisingly, the only variable that is significant is capacity in Thailand. The other variables are not significant for both Thailand and Taiwan.

Table 4 Tobit regression analysis testing pure technical inefficiency of rice mills in Thailand and Taiwan

	Thailand			Taiwan		
	Coefficient	**t-Statistic**	**Prob.**	**Coefficient**	**t-Statistic**	**Prob.**
YEAR OF ESTAB-LISHMENT	-3.61E-05	-0.015765	0.9874	0.001332	0.867249	0.3858
CAPACITY	-0.002115	-2.548747	0.0108	0.000625	0.979068	0.3275
$CAPACITY^2$	5.87E-06	2.024578	0.0429	-6.55E-07	-1.040824	0.2980
EXPERIENCE	0.006393	0.917783	0.3587	-0.018376	-0.668100	0.5041
$EXPERIENCE^2$	-0.000139	-0.814911	0.4151	-0.003020	-0.478629	0.6322
EDUCATION	-0.000925	-0.133257	0.8940	8.25E-05	0.627522	0.5303
ENERGY SOURCE	0.034196	0.877810	0.3800	-0.015596	-0.363776	0.7160
TYPE	0.095036	1.361160	0.1735	-0.004463	-0.072098	0.9425
C	0.836964	6.762458	0.0000	0.939352	7.575672	0.0000
Error Distribution						
SCALE:C(10)	**0.101788**	**7.335914**	**0.0000**	**0.110064**	**6.369745**	**0.0000**
R-squared	0.301364	Mean dependent var	0.874722	0.101464	Mean dependent var	0.910086
Adjusted R-squared	0.059528	S.D.dependent var	0.106213	-0.222010	S.D.dependent var	0.086244
S.E. of regression	0.103004	Akaike info criterion	-0.526726	0.095338	Akaike info criterion	0.061942
Sum squared resid	0.275853	Schwarz criterion	-0.086860	0.227233	Schwarz criterion	0.506327
Log likelihood	19.48108	Hannan-Quinn criter.	-0.373201	8.916018	Hannan-Quinn criter.	0.215344
Avg. log likelihood	0.541141					
Left censored obs	**0**	**Right censored obs**	**7**	**0**		**11**
Uncensored obs	**29**	**Total obs**	**36**	**24**		**35**

Source: Calculation.

6. Summary and Conclusions

The analysis of technical efficiency for the rice milling industry was conducted using Data Envelopment Analysis model. The results showed that the average of total technical efficiency and pure technical efficiency of rice mill in Thailand is less than Taiwan. The average CRS measure of technical efficiency is 84 % in Thailand and 87 % in Taiwan. The average VRS measure is 87 % in Thailand, compared to 91 % in Taiwan. This shows that efficiency of rice mills in Taiwan are clustered at the higher level than the rice mills in Thailand.

When technical efficiencies obtained with CRS and VRS models are equal then the operator is running under constant returns to scale. Scale efficiency results illustrated that 11.1 % and 11.4 % of the rice mills in Thailand and Taiwan respectively are operating at their optimal scale. Rice mill scale efficiency indices are about 96.3 % and 95.8% in Thailand and Taiwan, respectively. This implies that even if Taiwan has higher technical efficiency but the appropriate scale efficiencies of rice mill in both countries are almost identical. In addition, it can be mentioned that rice mills in Thailand and Taiwan, at least from the sample firms, are producing at an increasing return to scale. Therefore, these rice mills could increase their technical efficiency by continuing to increase their size.

The DEA results for each rice mill are also available to determine whether an individual rice mill can increase its technical efficiency by increasing or decreasing its inputs or whether it is already operating at optimal scale. The adjustments that can be made in the use of inputs by inefficient firms can be found by comparing them with their 'peer' firms. The composite of inputs on each decision making unit (DMU) was suggested how minimizing the use of excessive inputs could produce unchanged output.

Finally, this study attempts to identify factors inducing technical inefficiency of rice mills in both Thailand and Taiwan. The use of Tobit regression model to regress total technical efficiency on explanatory variables, defined as the number of years established, capacity of operation, experience, education level of rice miller, source of power, and dummy variable on type of business. The outcome from the analysis indicated that only the capacity in Thailand was significant.

Further investigation of factors affecting technical inefficiency is suggested to conduct.

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