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An Analysis on the Factors Affecting Rice Production Efficiency in Myanmar*

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The objective of this study is to obtain a better understanding of the current rice production condition in Myanmar through efficiency analysis, especially, to examine the impact of farm mechanization on Myanmar rice production efficiency. For representation of efficiency and the determinants, this paper uses both the data envelopment analysis (DEA) and the stochastic frontier approach (SFA) with variable returns to scale on Myanmar rice production. The efficiency of the rice production was estimated and subsequently the determinants factors were investigated based on the estimated efficiency level of these sample farmers. The empirical evidence finds that farm mechanical tools significantly improve the Myanmar rice production efficiency.

Keywords: Myanmar, Rice Farming, Farm Mechanization, Production Efficiency, Data Envelopment Analysis, Stochastic Frontier Approach
JEL Classification: D24, N55, O13

I. INTRODUCTION

Myanmar is a typical agriculture country, and possesses moderately natural resources which have underpinned the agricultural production. According to the published data in 2012, agricultural sector contributed 13.7% of total export

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earnings, shared GDP accounted for 37.8%, and employed 61.2% of the labor force in Myanmar (Department of Agricultural Planning, 2012). Due to the various agro-ecological conditions and large land area of Myanmar, several agricultural products have been produced abundantly. Among them, rice is the major crop for both economy and food security of the country. Therefore, efficient rice production would give more income and export revenue for the country because paddy production alone accounted about 35% of the total crop area in Myanmar. It would in turn allow Myanmar to make an essential step for construction of a developed country through reducing poverty, improving food security for all farms, fostering a more dynamic rural sector and making agriculture as a dynamic contributor to the national economy. Surely, all of these outcomes will be achieved only after framing and executing more effective policies at the sectorial and national levels.

Dapice et al.(2011) pointed out that the long-term trend in per capita rice production was reduced, which needs to reform and revitalization of agriculture required significant changes in policy through the stimulation of non-farm sectors so that they could absorb labor leaving agriculture. When looking back the history, Myanmar stood as major rice exporter in the world, but this role became dull due to various reasons in the recent days. Still, rice is the most important crop for Myanmar agriculture which dominates the largest and most productive part of the country economy. Myanmar still has great potential to increase rice production in various aspects such as land reclamations, effective mechanization and inputs, and good infrastructure development for both rural and urban areas.

There were several recent studies that focused on the estimation and explanation of agricultural efficiency in most of the Asian developing countries, e.g. in India (Battese and Coelli, 1992, Battese and Coelli, 1995), Thailand (Krasachat, 2004; Kiatpathomchai, 2008), Indonesia (Souires and Tabor, 1991: Brazdik, 2006), Pakistan (Shafiq and Rehman, 2000; Javed et al., 2008), Bangladesh (Rahman, 2003; Rahman, 2011), the Philippines (Villano and Fleming, 2004), and Vietnam (Tran et al., 1993; Huy, 2009; Khai and Yabe, 2011). All of these studies pointed out substantial inefficiency and the possible potentials to improve the agricultural productivity. However, there has been limited empirical attention on identifying the factors affecting improvement of rice production efficiency of Myanmar. There are many economic questions related to production efficiency of Myanmar rice farms which are still needed to be answered.

Myanmar is still lag behind in modern agricultural production, especially in the application of farm mechanization. The use of modern agricultural mechanical tools in rice production will raise productivity, reduce the processing time, and bring about the economy of scale. Mechanization not only increases land and labor productivity, but reduce the need for human and animal labor. At present, agricultural production is more or less traditional in Myanmar. Modernization and development of agricultural sector require the efficient use of farm mechanization tools. Thus, this study also investigates the role of farm mechanization in efficient rice production in Myanmar.

Myanmar has been exploring the use of farm machinery for crop cultivation instead of traditional cattle and manpower. However, the effort has not been entirely successful due to the lack of skills and experience. Continuous increases in the productivity and cropping intensity need the efficient utilization of machinery in farming from land preparation to harvesting and post harvesting activities. After independence, the government implemented agriculture mechanization schemes involving distribution of farm machinery to farmers. Even though the required machinery is produced and assembled locally or imported into the farm mechanization sector, the sufficient level has not been reached. The following table 1 describes the current utilization of farm machinery in Myanmar in the period of 2011-2012.

Table 1. Utilization of machinery and farm implements in Myanmar, 2011-2012

Types of Machinery	Number
Tractors	12,625
Power tiller	188,500
Mono wheel tractor	6,296
Cultivating roller boar	4,372
Threshing machine	38,384
Seeder	46,354
Harvester	3,220
Combine harvester	200
Water pump	178,424

Source: Department of Agricultural Planning, “Myanmar Agriculture in Brief, 2012”, MOAI.

The objective of this study is to obtain a better understanding of the current rice production efficiency in Myanmar, especially, to examine the impact of farm mechanization on production efficiency. The production efficiency of currently rice growing farmers is measured by using non-parametric analysis (data envelopment approach) and parametric analysis (stochastic frontier approach). After estimating the production efficiency, this paper subsequently investigates the determinants factors affecting the production efficiency of Myanmar rice farmers.

This paper is organized as follows. Section 1 gives some background information and section 2 provides the methodology related to the efficiency measures used in this study. Information about data and definition of the variables, and estimated results are presented in section 3 and 4, respectively. Discussions and the concluding remarks are drawn in section 5.

II. METHODOLOGY

Farrell's (1957) argued that measuring productive efficiency of an industry is important to both the economic theorists and the economic policy makers. In this study data envelopment analysis (DEA) and stochastic frontier analysis (SFA) are two alternative methods for measuring the efficiency of rice production in Myanmar. DEA involves the use of linear programming while SFA applies the econometric methods (Coelli et al., 1998).

1. Data envelopment analysis (DEA)

The basic DEA analysis requires two choices of formulation: choice of orientation and choice of envelopment surface. The choice of orientation or focus of analysis is possible through maximization of outputs or minimization of inputs or no orientation. The choice of envelopment surface is possible as constant return to scale CRS (conical hull) or variable return to scale VRS (convex hull) (Lovell, 1993). In this study, technical efficiency (TE) is calculated by using the output-oriented variable return to scale VRS DEA model, well-known as more flexible model. This study aims to know how much maximum output can be produced based on the current inputs usage. Therefore, it is assumed that output-oriented variable return scale model would be more appropriate in this study. Here, output variable used for estimating technical efficiency includes total rice production (Y). The inputs used in this study represent the paddy sown acres of individual farmer (X_1), number of total labor used in each farm (X_2), material costs of rice production (X_3), and operation costs (X_4), respectively. Following Coelli et al.(1998), an output oriented variable return to scale DEA model for technical efficiency was defined as:

$$\begin{gathered}\text{Max}_{\Phi,\lambda}\ \Phi, \\ \text{Subject to } -\Phi_{yi} + Y\lambda \geq 0 \\ x_i - X\lambda \geq 0 \\ N'\lambda = 1 \\ \lambda \geq 0 \end{gathered} \tag{1}$$

where Y represents an output for N farms, Φ represents the output technical efficiency score having a value $0 \leq \Phi \leq 1$, X represents an input matrix for N farms, λ is an Nx1 vector of weights which defines the linear combination of the peers of i^{th} farm. yi represents the total rice production of the i^{th} farm in baskets and x_i denotes the input vector of the i^{th} farm. X_{1i} represents paddy sown acreage (land) of individual farmers on the i^{th} farm, X_{2i} indicates the number total labors used on the i^{th} farm, X_{3i} represents the material costs of seeding and agrochemical application on the i^{th} farm, and X_{4i} shows the operation costs including the land preparation, harvesting and threshing activities expenses used on the i^{th} farm.

TE can be decomposed into two parts: pure technical efficiency and scale efficiency (SE). The pure technical efficiency can be drawn out from the technical efficiency by separating the scale effect. The VRS DEA is more flexible and envelopes the data more exactly than CRS DEA. Scale efficiency measure can be done by conducting both CRS DEA and VRS DEA. The decomposition obtained from the TE of the CRS DEA into two components: one is scale inefficiency and the other is pure inefficiency. There is a difference in the CRS and VRS efficiency scores for a farm, indicating the farm has scale inefficiency and it can be calculated from the difference between the VRS and CRS efficiency scores. A scale efficient farm has the same level of technical and pure technical efficiency. Based on the results of the TE scores, scale efficiency measure of each farm can be calculated simply as follows.

$$SE_i = TE_{iCRS}/TE_{iVRS} \tag{2}$$

where SE=1 implies scale efficiency and SE<1 implies scale inefficiency. However this scale efficiency measure cannot indicate whether the farm is operating in an area of increasing or decreasing returns to scale which can be captured by running an additional DEA problem with non-increasing return to scale (NIRS). Therefore, the return to scale analysis can be done by altering the DEA model in equation (1) by replacing the N1/ λ = 1 with N1/ λ ≤ 1, to provide;

$$
\begin{gathered}
\text{Max}_{\ \Phi,\lambda}\ \Phi, \\
\text{Subject to } -\Phi_{yi} + Y\lambda \geq 0 \\
x_i - X\lambda \geq 0 \\
N'\lambda \leq 1 \\
\lambda \geq 0
\end{gathered} \tag{3}
$$

The nature of the scale inefficiencies (increasing or decreasing returns to scale) can be pointed out by seeing whether the NIRS TE score is equal to the VRS TE score. If the NIRS TE score is equal to the VRS TE score, it indicates the increasing return to scale. On the other hand, if the scores are unequal, it is decreasing return to scale. Note that the constraint N'λ ≤ 1 means the ith firms cannot be captured which are larger than 1, but it may be compared with firms smaller than it. Here, DEAP 2.1 software program developed by Coelli[1] was used to conduct data envelopment analysis.

Next, in order to examine the influence factors that can hinder the rice production efficiency, tobit regression analysis is used as a second stage of the relationship between the technical efficiency measure and other relevant variables. Tobit analysis, a model devised by Tobin (1958), assumed that the dependent variable has a number of its values clustered at a limiting value, usually zero. Because the ordinary least square (OLS) regression is not appropriate for this regression analysis that the technical efficiency score is limited between 0 and 1, the dependent variable does not have normal distribution. Tobit regression is more convenient to have data censored at zero that at 1. This study employs the following tobit regression model and expresses as follow:

$$
\begin{gathered}
TE_i = TE_i{}^* = \beta_0 + \beta_1 Z_{1i} + \beta_2 Z_{2i} + \beta_3 Z_{3i} + \beta_4 Z_{4i} + \beta_5 Z_{5i} + \beta_6 Z_{6i} + \mu_i \\
if \quad TE_i > 0 \ (or) \ TE_i = 0, \ if \quad TE_i \leq 0
\end{gathered} \tag{4}
$$

[1] "A Guide to DEAP Version 2.1: A Data Envelopment Analysis(Computer) Program," CEPA Working papers, Department of Econometrics University of New England.

where, i refers to the i^{th} farm in the sample.
TE_i is an efficiency measures representing technical efficiency of the i^{th} farm.
TE_i* is the latent variable.
Z_{1i} expresses age of the farm household head of the i^{th} farmers
Z_{2i} expresses the square of age
Z_{3i} is denotes an educational category variables of farmers for their respective education levels
Z_{4i} specify the shared of family labor ratio on the total labor used
Z_{5i} represents the dummy value off-farm income except rice: 1 for having off-farm income and 0 for otherwise
Z_{6i} is the numbers mechanical tools using in farming operations in this area
β's are unknown parameters to be estimated
μ_i is the error term

2. Stochastic frontier analysis

It has been accepted that econometric was estimating the average production function before the pioneering work of Farrell (1957) that has brought the possibility of estimating so-called frontier functions, in an effort to bridge the gap between theory and empirical work. The econometric approach is stochastic and parametric. Continuing the Farrell works, Aigner et al. (1977) and Meeusen and van den Broeck (1977) independently suggested a new approach to the estimation of stochastic frontier analysis (SFA) function as a parametric analysis. Stochastic estimations incorporate the estimation of a stochastic production frontier where the output of a firm is a function of a set of inputs, inefficiency, and random error.

According to Coelli and Battese (1996), stochastic frontier production function approach has generally been preferred in agricultural economic literature. This is probably related to a number of factors. The assumption that all the deviations from the frontier are associated with inefficiency, as assume in DEA, is difficult to be accepted in SFA, given the inherent variability nature of agricultural production due to weather, fires, pests and diseases etc. Furthermore, because many farms are small family-owned operations, the keeping of accurate records is not always a priority. Thus much available data on production are likely to be subjected to measurement errors. This approach has the advantage of being statistical and hence permitting the testing of reliability of the model estimated. It can measure the marginal contribution of each type input to aggregate output.

Moreover, tests of hypotheses regarding the existence of inefficiency and the structure of the production technology can be performed in SFA (Coelli et al., 1998).

There are a number of functional forms used in the frontier analysis. In order to select the best specification for the production function (Cobb-Douglas or Translog) for the given data set, we conducted the Likelihood-Ratio (LR) test after estimation of the two stochastic production frontier models. This study observed that stochastic frontier translog production function was more preferable compared to stochastic frontier Cobb-Douglas production function[2]. The translog functional form for the stochastic frontier has been widely adopted in frontier studies, because this functional form is flexible and computationally straightforward (Kwon and Lee , 2004; Kang, 2005). The general form of the translog form with time-invariant model of stochastic frontier used in this study is described as follow.

$$\ln y_{it} = \beta_0 + \sum_{j=1}^{4} \beta j \ln x_{jit} + 0.5 \sum_{j=1}^{4} \sum_{k=1}^{4} \beta_{jk} \ln x_{jit} \ln x_{kit} + v_i - u_i \quad (5)$$

where, i indicates an observation for the i^{th} sample farmer in the survey, i = 1, 2, …, n, y_i represents the total rice production of the i^{th} farm expressed in baskets, x_j and x_k are the quantity of inputs used in rice production; and j and k = paddy sown acreage (land) of individual farmers on the i^{th} farm; the number total labors used on the i^{th} farm; the material costs of seeding and agrochemical application on the ith farm; the operation costs including the land preparation, harvesting and threshing activities expenses used on the ith farm. $\beta_{jk} = \beta_{kj}$ are parameters to be estimated and v_is are assumed to be independent and identically distributed as normal random variables following an *iid* normal distribution of zero mean and variance of σ_v2, independent of the u_is; σ_u2, u_is represents non-negative technical inefficiency of i^{th} producers which are also assumed to be non-negative, independently distributed as truncations at zero.

2 The values of the log likelihood for the Cobb-Douglas and Translog production frontiers are 150.93 and 174.50, respectively. The value of the Likelihood-Ratio (LR) test equals to 21.65 and it is statistically significant at the 1% significance level, indicating that translog production function is more preferable than Cobb-Douglas production function.

Although the SFA model was originally proposed for the analysis of the panel data by Battese and Coelli (1995), a general SFA function for the cross-sectional data is also considered. They extended the stochastic production frontier model by suggesting that the inefficiency effects can be expressed as a linear function of explanatory variables, reflecting farm-specific variables. The determinants of technical inefficiencies can be obtained by regressing the estimated inefficiency effects resulted from an estimated stochastic frontier, upon a vector of farm-specific factors (such as demographic variables of individual farm). This is a two-stage approach: first, the inefficiency effects are assumed to be independently and identically distributed and second, the predicted inefficiency effects are assumed to be a function of a number of farm-specific factors, which implies that they are not identically distributed, unless all the coefficients of the factors are simultaneously equal to zero. The inefficiency effects model proposed by Battese and Coelli (1995) are assumed to be independently (but not identically) distributed non-negative random variables. The technical inefficiency effect model is described by:

$$u_{it}=\delta_0+\delta_i z_{it} \tag{6}$$

where u_{it}, the technical inefficiency effects, are assumed to be a function of explanatory variables, z_{it} is a vector of observed explanatory variables related to the technical inefficiency effects in the t^{th} period and δ is a vector of unknown parameters to be estimated. Here, the determinants of the explanatory variables are described as follow. They are the same variables as in non-parametric approach.

This model assumes the normal distributions, which are truncated at zero to obtain the distributions of the technical inefficiency effects.

III. DATA AND VARIABLES

Data were collected from a cross sectional survey of rice-specific farmers in the township of Bogalay, Irrawaddy division, Myanmar in December, 2012. Twenty nine villages among fifty village-tracts were selected by simple random sampling because the population was heterogeneous with respect to different agro-ecological zones and farm size. The data gathered for the 2012 rice growing seasons include monsoon paddy and summer paddy productions. The questionnaire was constructed to ask for details about rice production at the individual farms and they have similar level of rice production technology except various level of input used and management skill. In particular, there was interest in the area grown, the yields obtained, and the use of inputs, such as labors, fertilizer, seed, and pesticides. Information was also obtained on demographic variables of the sample farmers. Data on a total of 220 sample farmers of both summer and monsoon paddy production were obtained in the survey. After removing the missing data, 195 farmers were finally taken into account in this study.

Table 2 describes the selected characteristics of the variables used in the efficiency measures. Here, each farm household is aggregated for their respective output and inputs used in rice production for both summer and monsoon paddy. For each farm household, data are aggregated into one output and four input variables. The output represents the total un-husked rice production of the individual farms which is measurd in basket. The average total rice production is about 940 baskets per farm with a range of minimum 120 baskets up to maximum 4,340 baskets of each farm production for both seasons. The input data are aggregated into four categories: (i) rice growing area, (ii) labor, (iii) materials, and (iv) other input. The data collected on inputs are in quantity for land and labor while the value terms for materials and other input.[3]

Sown area includes the combine area planted of rice for each sample farm for both summer and monsoon paddy cropping seasons when the survey is done. This variable is particularly measured in acres. The average value of rice growing area per farm is 14.4 acres (approximately 5.24 ha) with a range of 2 to 62 acres in this survey area. Labor measured the total labor used in rice production activities including the numbers of family labor and permanent hired labor for each farm.

[3] The material and operation expenditure data are deflated using respective input-specific purchasing price indices. Use of expenditure input data is a concern. When input prices vary systematically (changing in real terms), our data in value terms would systematically bias the estimation results. That is, prices lower than national prices result in the overestimation of efficiency. However, given that only material inputs are measured in value terms (excluding inputs such as labour and land that might exhibit significant regional differences) and input specific price trends are removed, it is believed that the magnitude of estimation bias would be small(Kwon and Lee, 2004; Kang, 2005).

Table 2. Descriptive statistics of output and inputs based on each sample farm

Variables	Unit	Mean	Standard deviation	Minimum	Maximum
Paddy production	Basket	940.13	631.11	120	4,340
Sown area	Acre	14.40	9.29	2	62
Labor	Person	5	1.55	2	12
Materials	Kyats	887,291	601,198	101,700	4,179,850
Other input	Kyats	488,359	338,305	72,800	2,600,900

Note: "Kyats" is the Myanmar currency and one dollar is equal about 900 Kyats during 2011~2012.
Source: Calculated from the survey data.

The mean value of labor used per farm is 5 persons with a minimum 2 to a maximum labor of 12. The materials represent the cost of materials used in farming which represents the expenses on seeding and agrochemical used for each farm. The seeding cost is calculated based on seed cost and application cost. There are two types of seeding method in this area: direct seeding and transplanting. Some sample farmers used direct seeding method and transplanting either independently or a combination of both. Mostly, direct seeding method is used in high-yielding varieties (HYV) and summer season paddy production. So, the seeding costs include total expenses on seeding and its application costs too.

As the government has pursued market liberalization policy, there have no subsidy plans of price and input to farmers. It is said that the inputs prices were not different since most of the private companies distributed fertilizer directly to farms in the survey area. Fertilizer cost is measured as the total expenditure on fertilizer kilogram. The mean value of the materials varies from 101,700 to 4,179,850 Kyats per farm. In the case of other input, it is calculated based on the summing of land preparation cost, harvesting and threshing costs, respectively. Here, the average value is 488,359 Kyats with a range from 72,800 to 2,600,900 Kyats per farm.

The data used in the second stage regression analysis comprise the farm specific variables which are assumed to have some influence on the efficiency of those rice farms presented in table 3. The farm specific variables are considered; age of the farm operators, education levels of the farm operators, family labor ratio in total labor used in rice production, off-farm income and the amount of mechanical tools used in rice farming.

Table 3. Socioeconomic variables of the sample farmers

Variables	Unit	Mean	Standard deviation	Minimum	Maximum
Farmer's age	Year	50	12	23	77
Farmer's Education level	Category variable	1.44	0.76	0	4
Number of family	Person	5	2	1	11
Off-farm income	Dummy variable	0.43	0.50	0	1
Farming assets					
Plough	Number	0.53	0.53	0	2
Harrow	Number	0.14	0.43	0	3
Bullock	Number	0.37	0.90	0	5
Power tiller	Number	0.44	0.54	0	3
Seeder	Number	0.01	0.10	0	1
Sprayer	Number	0.44	0.54	0	2
Water pump	Number	0.41	0.51	0	2
Threshing machine	Number	0.38	0.50	0	2
Ware house	Number	0.44	0.51	0	2

Note: Zero represents the non-use of the corresponding variable. Education levels identified 0, 1, 2, 3, and 4 representing illiterate, primary, secondary, high school and graduate levels, respectively. Off-farm income dummy specified 0 for no off-farm income and 1 for having off-farm income.
Source: Calculated from the survey data.

The mean value of the age of farm operator is 50 years with a range of 23 to 77 years, showing a high variability of ages among farmers. Accordingly, most of the farm operators possess the average education level, not more than the secondary school level; it shows about 1.5 levels of the educational category variables. The number of each farm family reveals 5 persons in average with a range of 1 to 11 persons. Off-farm income dummy variables of 0.43 indicate that 60 percent of the farm families do not participate in off-farm income activities in this sample area. Moreover, the summary statistics of the farming assets representing the farm equipment and machineries tools used in rice cultivation activities are also displayed in this table.

IV. EMPIRICAL RESULTS

1. Data envelopment analysis measure

The result of output-oriented technical efficiency indexes of the sample rice producing farmers is displayed in table 4. Here, the average overall technical efficiency (CRS-TE) is 63% with a minimum level of 44% and maximum level of

100%. Then, the pure technical efficiency (VRS-TE) results the mean index of 69% with a range of 46% up to 100%. Similarly, the observation of scale efficiency finds 92% of average value with a minimum value of 55% and a maximum value of 100% of the sample farmers. It is evident from the results that the majority of the sample farmers' overall technical efficiency indexes and the pure technical efficiency indexes are fallen within the range of 0.51 and 0.70.

Table 4. Frequency distribution of technical efficiency index from DEA approach

Efficiency Level	Technical Efficiency					
	CRS-TE (Overall TE)		VRS-TE (Pure TE)		Scale Efficiency	
	Number of farm	%	Number of farm	%	Number of farm	%
0.01 - 0.10	0	0%	0	0%	0	0%
0.11 - 0.20	0	0%	0	0%	0	0%
0.21 - 0.30	0	0%	0	0%	0	0%
0.31 - 0.40	0	0%	0	0%	0	0%
0.41 - 0.50	16	8%	5	3%	0	0%
0.51 - 0.60	82	42%	51	26%	4	2%
0.61 - 0.70	58	30%	70	36%	5	3%
0.71 - 0.80	20	10%	34	17%	5	3%
0.81 - 0.90	12	6%	13	7%	34	17%
0.91 - 1.00	7	4%	22	11%	147	75%
Mean TE	0.63		0.69		0.92	
Minimum TE	0.44		0.46		0.55	
Maximum TE	1.00		1.00		1.00	

Source: Calculated from survey data.

The impacts of the factors which could have influenced the rice technical efficiency are analyzed by using the Tobit regression model. This model was applied to VRS-TE as a dependent variable and some key socio-economic independent variables related to technical inefficiency. Table 5 displays the results of Tobit regression function for the technical efficiency. The technical efficiency scores are regressed against the age of the farm household head, educational level, off-farm income dummy, labor ratio, mechanical tools used in farming operations.

The results showed that age of the sample farmers' has a negative, but a positive quadratic effect on efficiency indexes even though it is not significant related to the technical efficiency indexes. The category variables of education level of the farm operators are negatively and significantly related at 10% level to the efficiency scores. Here the education variables represent only for the primary and illiterate education levels. Alternately, it can be said that the technical efficiency will be increased if the head of households possess higher education level. As expected, the share of family labors included in the total number of labors has positively and significantly related to the technical efficiency scores. This tends to show that the more intensive the family labors in rice production, the higher the efficiency of production for the sample households. Then the off-farm income variable is negatively related to the efficiency indexes and showed that the lesser off-farm income work can increase the efficiency of rice production in this area.

Subsequently, the next variable is the mechanical tools used in farming activities, which is positive and significantly related to the efficiency indexes at 5% level of significant. It means one more unit of mechanical tools used in rice production; the efficiency score will increase approximately 1%. The utilization of mechanical tools displays the increase in efficiency in this sample area. Agricultural mechanization includes the use of tools, implements and machines for enhancing productivity by precision and efficient placement of inputs. Even though the sample area was devastated by Cyclone Nargis in 2008 and most of the farmers lost their agricultural mechanical tools during this time, the result of the analysis showed the important role of these mechanical tools in efficient rice production.

Table 5. Result of Tobit regression coefficients

Variables		Coefficients
Age	β1	- 0.00966 (0.00076)
Age2	β2	0.00009 (0.00006)
Education category variable	B3	- 0.04376 (0.02465)*
Family labor ratio	B4	0.10949 (0.04472)**
Off-farm income	B5	- 0.00395 (0.02266)*
Mechanical tools	B6	0.01093 (0.00432)**
Constant	β0	0.85636 (0.14308)***
Wald Chi2 (6): 14.53 Log likelihood: 85.783107**		

Note: 1) *, **, and *** indicate significance at the 10%, 5% and 1% level, respectively.
2) Standard deviations of estimates are expressed in parentheses.
3) The education category variables represent the education level of farm operators' up to the secondary level of education; above secondary education levels is dropped as the reference education dummy variable. The family labor ratio variable represents the share of family labor on total labors used in rice production.

2. Stochastic frontier analysis measure

Table 6 shows the distribution of the technical efficiency resulted from the maximum likelihood estimates of the parameters based on normal/truncated normal distribution of analysis of stochastic frontier function (variable return to scale) of the sample farmers. The estimates for technical efficiency index show that on average farmers are 78% efficient with a range of minimum 69% up to maximum 100%, implying that the average farms produced 78% of the maximum attainable output for a given input levels. On the other hand, based on the efficiency results, technical efficiency of the sample rice farmers in these areas could increase by 22% based on their current production conditions. In the case of percentage distribution, most of the sample farmers, 57%, fall under the efficiency index of 0.71~8.0, followed by 27% under 0.81~0.90, 11% for 0.61~7.00 and 5% of the sample farmers got the highest efficiency index between 0.91~1.00.

Table 6. Frequency distribution of the efficiency index from SFA approach

Efficiency level	Frequency	Percentage
0.01 - 0.10	0	0%
0.11 - 0.20	0	0%
0.21 - 0.30	0	0%
0.31 - 0.40	0	0%
0.41 - 0.50	0	0%
0.51 - 0.60	0	0%
0.61 - 0.70	21	11%
0.71 - 0.80	112	57%
0.81 - 0.90	52	27%
0.91 - 1.00	10	5%
Mean TE	0.78	
Minimum TE	0.69	
Maximum TE	1.00	

Source: Calculated from survey data.

The maximum likelihood estimates of the parameters employ the translog functional form that has been widely adopted in frontier studies. To examine the technical efficiency, the translog production frontier is estimated by maximum likelihood assuming a truncated normal distribution for ui. Table 7 presents the estimated parameter results of the frontier function. The wald-chi square test for the significance of the regression rejects the null hypothesis that the parameter coefficients of the explanatory variables are all zero at the one % level. The variance parameters σ2 and γ are different from zero means that there are differences in technical efficiency among farmers.

Table 7. Result of parameters estimate of the stochastic frontier function

Variable		Coefficient	Standard error
lnXA	β1	7.2965	7.0015
lnXL	β2	- 2.6145*	3.3344
lnXM	β3	- 1.4064	3.6601
lnXO	β4	- 2.0908	4.9950
0.5lnXAlnXA	β5	0.8056*	0.7183
lnXAlnXL	β6	- 0.1470***	0.3005
lnXAlnXM	β7	- 0.3905***	0.3824
lnXAlnXO	β8	- 0.2486	0.4899
0.5lnXLlnXL	β9	0.0071***	0.2477
lnXLlnXM	β10	0.3633***	0.2705
lnXLlnXO	β11	- 0.1487***	0.1967
0.5lnXMlnXM	β12	0.1350**	0.3520
lnXMlnXO	β13	0.0100***	0.2862
0.5lnXOlnXO	β14	0.2302**	0.4033
Constant	β15	27.0123***	35.1936
Variance parameters	σ2	0.0098	
	Γ	0.0222	
Wald Chi2 (14): 2829.23***			
Log likelihood: 174.50			

Note: 1) *, **, and *** indicate significant at the 10%, 5% and 1% level, respectively.
2) XL, XM and XO are the inputs of labor, material cost and operational cost, respectively and these variables are divided by the land variable of the rice production sample farms.

Subsequently, the regression results for the determinants of technical inefficiency are displayed in table 8. The efficiency determinants are estimated with the production frontier simultaneously. Here, technical inefficiency scores, as measured relative to the technically efficient producers, are regressed against the determinant factors of explanatory variables such as the age of the farms' household head, education levels, family labor ratio, off-farm income, and mechanical tools which are the same variables used in non-parametric analysis. It can be seen that the results signs of all the determinants variables are similar to the results from the DEA analysis except the off farm income and ratio of family labor variables. However, the share of family labor and the off-farm income variables are statistically insignificant in this result.

Importantly, it can be seen that the number of the mechanical tools used in rice farming variable is negatively and significantly related to the technical inefficiency at 1% level. It is suggested that 100% increase in the use of mechanical tools in rice production would increase the efficiency by 2.4%.

Table 8. Result of the parameters determinants on technical inefficiency index

Variables		Coefficients
Age	β1	0.00620 (0.0046)
Age2	β2	- 0.00006 (0.00004)
Education category variable	β3	0.05648 (0.01890)**
Family labor ratio	β4	0.02429 (0.03622)
Off-farm income	β5	- 0.025548 (0.01771)
Mechanical tools	β6	- 0.02434 (0.00455)***
Constant	β0	0.11567 (0.14989)*

Note: 1) *, **, and *** indicate significant at the 10%, 5% and 1% level, respectively.
2) Standard deviations of estimates are expressed in parentheses.
3) The education category variables represent the education level of farm operators' up to the secondary level of education; above secondary education level is dropped as the reference education dummy variable. The family labor ratio variable represents the share of family labor on total labors used in rice production.

V. CONCLUSIONS

The purpose of this study is to obtain a better understanding of the current rice production efficiency and to find out the determinants factors which can influence the rice production efficiency, especially focusing more on the impact of farm mechanization. Based on the caution required in interpreting the results, the general conclusions for the sample rice farms can be drawn. The results from DEA approach showed that the average technical efficiency values are 63% with CRS-TE and 69% with VRS-TE scores, respectively. It implies that the average technical inefficiency ranges from 31% to 37% indicating that there is a potential to improve the existing technical efficiency of the sample farmers without reducing both the levels of input used and the existing technology. According to the theoretical assumption of the non-parametric approach, the farm which possesses the highest efficiency score is situated on the production frontier line. Therefore, the estimated results from non-parametric approach indicate that the inefficient samples farmers can improve their rice production efficiency to catch up the efficient sample farmers in these regions.

Thereafter, the determinants factors which influence the technical efficiency of the sample farmers are discussed. In Myanmar, farmers are not easily adopting the modern technologies and also they do not want to discard their traditional customs and practices. The educational category variables which represent only for illiterate and primary level of education of the farm households' head and technical efficiency are negatively and significantly related. According to these results the lower education levels of the farm operators seem to have lower efficiency scores. In contrast, highly educated operators are more likely to improve technical efficiency which agrees with Ajibefun (2008) who reported that education is expected to make farmers less conservative and more respective to new technology and innovation, which will consequently lead to higher technical efficiency. Therefore, increasing private and public investment in education might lead to better improvement in agricultural sector.

It is found that in this study the value of using family labor might be more efficient given the result of the scarcity of employed seasonal labor especially during the peak cultivation time in this study. Based on this finding, the rice farming in Myanmar should consider the role of modernized farm mechanization system which is accomplished by the systematic land reclamation condition. At present, in Myanmar the structure of agricultural land is very fragmented and this condition has obstructed the efficient modernized farm mechanization system. According to the study of Korean agriculture by Kang (2004), a high level of production efficiency resulted from the larger farms and greater human capital. Based on this fact, Myanmar agricultural development can be obtained through not only application of farm mechanization but farm consolidation in order to improve productivity and competitiveness. In order to leap forward for a developed farming, the applications of modernized farming machineries are essential. It can improve not only the production efficiency in farming but also mass production. Therefore, the policy makers should consider the role of farming machinery as an important issue.

As an alternative version of measuring the technical efficiency, parametric analysis, stochastic frontier analysis with translog functional form was applied in this study. The translog production function has been widely used in empirical analysis because of its flexible property in modeling. The input-output data of the individual sample farmers in this analysis were same variables as in non-parametric approach. The technical efficiency of parametric analysis in this study showed higher efficiency indexes than non-parametric analysis. The overall mean value of efficiency index is 0.78, indicating that the average farm produced only 78% of the maximum attainable output for a given input levels[4]. The sample farms covered a range of minimum value from 0.69 to a maximum value to 1.00 of efficiency indexes too. This result suggested that the average farm technical efficiency could increase by 22% under the existing production operations. Additionally, the variance parameters σ^2 and γ expressed again inefficiency effects in this analysis. The current using technological practices and input usages are still not sufficient to ensure the fully efficient production in these areas.

Simultaneously, the results of the determinants of the technical inefficiency can be seen with this production frontier model. In this analysis, technical inefficiency indexes is used as regressand and the determinants of the technical inefficiency (regressors) variables in this analysis are the same variables as DEA approach. Among the all regressors, the variables such as education category and mechanical tools were significantly associated with the inefficiency scores in the parametric approach. And also, the signs of correlation directions are also the same with the outcomes of non-parametric approach except family labor ratio and the off-farm income variables.

Above all, there are many constraints for a modernized mechanization farming system in Myanmar such as small sized farms, maintenance of machines and financial status, etc. So the current study reveals all of these limited conditions of Myanmar farmers. Special emphasis should be placed on better living standard of farmers and agricultural development for further enhancing national strength Development of rice sector industry which is the basic foundation for agriculture sector will require investment in infrastructure to drive agricultural growth and productivity. Therefore, the decision makers of Myanmar should give more emphasis on infrastructure development and modernized farming system than the current conditions.

[4] As a result of this study, more recent studies find that SFA efficiency scores are generally higher compared to DEA scores. This may reflect the different treatment of stochastic noise and the ability to control for heterogeneity (Fiorentino et al., 2006).

This paper focuses on the empirical investigation of the factors affecting rice production efficiency in Myanmar, using the efficiency scores generated by the parametric and nonparametric methodologies. While DEA does not make accommodation for statistical noise such as measure error, SFA makes accommodation for statistical noise such as random variables of weather, luck and other events beyond the control of farms, and measures error. However, both DEA and SFA are efficiency frontier analysis, and provide a suitable way of measuring the production efficiency. On the other hand, this study has a limitation that those results from DEA and SFA are not compared with each other through the statistical verification such as a consistency test.

Empirical analyses of issues related to farm efficiency using Myanmar farm-level data may generate useful information for policy makers. Especially, knowledge of factors driving rice production efficiency and contributions of production efficiency to economic performance could provide support for policies facilitating shifts in these directions.

REFERENCES

Aigner, D. J., Lovell, C. A. K. and P. Schmidt. 1977. "Formulation and Etimation of Stochastic Frontier Production Function Models," *Journal of Econometrics,* vol. 6, no. 1, pp. 21-37.

Ajibefun, I. A. 2008. "An Evaluation of Parametric and Non-parametric Methods of Technical Efficiency Measurement: Application to Small Scale Food Crop Production in Nigeria," *Journal of Agriculture and Social Sciences*, vol. 4, no. 3, pp. 95-100.

Battese, G. E. and T. J. Coelli. 1992. "Frontier Production Functions, Technical Efficiency and Panel Data: With Application to Paddy Farmers in India," *Journal of Productivity Analysis,* vol. 3, no. 1-2, pp. 153-169.

________________________. 1995. "A Model for Technical Efficiency Effects in a Stochastic Frontier Production Function for Panel Data," *Empirical Economics*, vol. 20, no. 2, pp. 325-332.

Brazdik, F. 2006. "Non-parametric Analysis of Technical Efficiency: Factors Affecting Efficiency of West Java Rice Farms," CERGE-EI Working Paper Series No. 286.

Coelli, T. J. and G. E. Battese. 1996. "Identification of Factors which Influence the Technical Efficiency of Indian Farmers," *Australian Journal of Agricultural Economics,* vol. 40, no. 2, pp. 103-128.

Coelli, T. J., Rao, D. S. P. and G. E. Battese. 1998. *An introduction to efficiency and productivity Analysis.* Boston: Kluwer Academic Publishers.

Dapice, D. O., Valley, T. J. and B. Wilkinson. 2011. *Myanmar agriculture in 2011: Old problems and new challenges.* Ash Center for Democratic Governance and

Innovation, Harvard Kennedy School.
Department of Agricultural Planning, Ministry of Agriculture and Irrigation. 2012. *Myanmar agriculture at a glance 2012, DAP, MOAI, Myanmar.*
Department of Agricultural Planning, Ministry of Agriculture and Irrigation. 2012. *Myanmar agriculture in brief 2012, DAP, MOAI, Myanmar.*
Farrell, M. J. 1957. "The Measurement of Productive Efficiency," *Journal of the Royal Statistical Society*. Series A(Gerneral), vol. 120, no. 3, pp. 253-290.
Fiorentino, E., Karmann, A. and M. Koetter. 2006. "The Cost Efficiency of German Banks: A Comparison SFA and DEA," Deutsche Bundesbank Discussion Paper, Series 2: Banlcing and Financil studies, no. 10/2006.
Huy, H. T. 2009. "Technical Efficiency of Rice Producing Households in the Mekong Delta of Vietnam," *Asian Journal of Agriculture and Development,* vol. 6, no. 2, pp. 35-50.
Javed, M. I., Adil, S. A., Javed, M. S. and S. Hassan. 2008. "Efficiency Analysis of Rice-wheat System in Punjab, Pakistan," *Pakistan Journal of Agricultural Science,* vol. 45, no. 3, pp. 95-100.
Kang, H. J. 2004. Consolidation and Productivity in Korean Agriculture: Analysis of Farm-level Panel Data. Ph. D. Dissertation, University of California Davis.
_________. 2005. "The Impact of Farm Consolidation on Productive Efficiency in Korean Agriculture: Analysis of Farm-level Panel Data," *Korean Economic Review,* vol. 21, no. 1, pp. 147-162.
Khai, H. V. and M. Yabe. 2011. "Technical Efficiency Analysis of Rice Production in Vietnam," *Journal of International Society for Southeast Asia Agricultural Science*, vol. 17, no. 1, pp. 135-146.
Kiatpathomchai, S. 2008. Assessing Economic and Environmental Efficiency of Rice Production Systems in Southern Thailand: An Application of Data Envelopment Analysis. Ph.D. Dissertation, University of Giessen.
Krasachat, W. 2004. "Technical Efficiency of Rice Farms in Thailand: A Non-parametric Approach," *Journal of American Academy of Business*, vol. 4, no. 1-2, pp. 64-69.
Kwon, O. S. and H. Lee. 2004. "Productivity Improvement in Korean Rice Farming: Parametric and Non-parametric Analysis," *Australian Journal of Agricultural and Resource Economics*, vol. 48, no. 2, pp. 323-346.
Lovell, C. A. K. 1993. "Production Frontiers and Productive Efficiency," In Fried, H. O. et al. (eds.) *The measurement of productive efficiency: techniques and application.* New York: Oxford University Press.
Meeusen, W. and J. van den Broeck. 1977. "Efficiency Estimation from Cobb-Douglas Production Functions with Composed Error," *International Economic Review*, vol. 18, no. 2, pp. 435-444.
Rahman, S. 2003. "Profit Efficiency among Bangladeshi Rice Farmers," *Food Policy,* vol. 28, no. 5-6, pp. 487-503.
_________. 2011. "Resource use Efficiency under Self-selectivity: The Case of Bangladeshi Rice Producers," *Australian Journal of Agricultural and Resource Economics,* vol. 55, no. 2, pp. 273-290.

Shafiq, M. and T. Rehman. 2000. “The Extent of Resource use Inefficiencies in Cotton Production in Pakistan’s Punjab: An Application of Data Envelopment Analysis,” *Agricultural Economics*, vol. 22, no. 3, pp. 321-330.
Souires, D. and S. Tabor. 1991. “Technical Efficiency and Future Production Gains in Indonesian Agriculture,” *Developing Economies,* vol. 29, no. 3, pp. 258-270.
Tobin, J. 1958. “Estimation of Relationships for Limited Dependent Variables,” *Econometrica*, vol. 26, no. 1, pp. 24-36.
Tran, S., Coelli, T. J. and E. Fleming. 1993. “Analysis of the Technical Efficiency of State Rubber Farms in Vietnam,” *Agricultural Economics,* vol. 9, no. 3, pp. 183-201.
Villano, R. and E. 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 Paper no. 2004-15, Series in Agricultural and Resource Economics, University of New England.

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