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Measuring the efficiency and determinants of rice production in Myanmar: a translog stochastic frontier approach

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Abstract

This study investigated the extent to which rice producers from the Ayeyarwaddy Region of Myanmar could improve their productivity if inputs were used efficiently in rice cultivation. To achieve this objective, simple random sampling was used to collect data from 300 rice growers in the study area. Data were analyzed with the translog stochastic frontier approach to understand the production efficiencies. The study further estimated the influencing factors that affect the efficiency levels of rice farmers. The empirical result reveals that the average technical, allocative, and economic efficiencies were at 76.11, 47.85, and 34.15%, respectively. This suggests that there is considerable room for improving rice production by better utilization of the available resources at the current level of technology. This study suggests that strenthening agricultural training programs and adoption of improved rice varieties may reduce overall inefficiencies among rice farmers in Myanmar. Factors like age, household size, education, farming experience, farm size, rice variety, training, and off-farm income have a significant impact on increasing/decreasing farmer's efficiency. Efficiency can be improved by establishing farmer field school programs to increase the scale of operations. The government should encourage young educated people to participate in paddy production and also intervene to reduce input prices and control the quality of seeds.

Keywords: Myanmar, production efficiencies, rice farmers, translog stochastic frontier approach

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Introduction

Agriculture plays a major role in Myanmar's society by providing employment and income for a growing population as well as by ensuring food security at both the community and national levels. Among the agricultural crops, production of rice contributes the highest (about 54%) of total net sown area (2017 - 2018). Ayeyarwaddy Delta Region is one of the main-surplus rice-producing areas where the ecological environment is favorable for rice production and supplies mainly to the domestic and the international markets. It has a monsoon climate with an average rainfall of about 2,500 mm annually and an average temperature of 32°C. The majority of rice production in the delta region contributed about 28.13% of the total area grown to rice in 2018 - 2019. In this region, total rice sown areas were increased from 4.9 million acres in 2014 - 2015 to 5.13 million acres in 2017 - 2018. Yield per acre was also slightly decreased from 1585.36 $kg \cdot ac^{-1}$ in 2014 - 2015 to 1564.50 $kg \cdot ac^{-1}$ in 2017-2018. Due to the expansion of sown areas, paddy production was increased from 7.12 million tons in 2014 - 2015 to 7.83 million tons in 2017 - 2018 (CSO, 2019). There has been no significant increase in rice production in the last decade as paddy yields have remained unchanged and then rice yield and production in Myanmar remain low compared to neighboring countries. It is important to consider the efficiency of resource use among farmers in order to analyze the actual productivity of rice production in Myanmar. The best and most effective way to increase rice productivity is to use scarce resources more efficiently.

In order to increase rice production, farmers need to adopt modern technologies such as new technological innovations, good farming practices and so on. As such, increasing productivity through more efficient utilization of the available existing scarce resources is more reasonable and cost-effective than introducing new technologies (Bravo-Ureta and Pinheiro, 1997). Efficiency analysis is related to the probability of farms producing a certain optimum level of output at the least cost in general.

In this study, we firstly evaluated the technical, allocative and economic efficiency using stochastic translog frontier approach. Then, we determined the factors that influence the efficiency of rice production in the study area. This study has drawn some policy implications through the estimated model and production efficiency estimates for improving rice productivity in Myanmar.

There are two common methods of efficiency measures, namely stochastic frontiers analysis (SFA) and data envelopment analysis (DEA), which comprise econometric methods and mathematical programming, respectively. SFA function has been widely used for agricultural studies due to its advantages compared to DEA. The main strengthen of SFA is that it deals with stochastic noise and conducts statistical tests of hypotheses regarding production structure and the degree of inefficiency. The weakness of this approach is the need to impose a functional form for the underlying technology and the distribution assumption for the inefficiency term of the composite error term. The main advantages of the DEA approach are that there is no parametric specification of technology as well as the distributional assumption for the inefficiency term. Nonetheless, it is deterministic and ignores the stochastic error term which attributes to all the deviations from the frontier to inefficiencies. Hence, SFA is more appropriate than DEA in this study.

There have been many empirical studies applying the SFA methodology for estimating production efficiency to agricultural research over the years. For example, Magreta et al. (2013), Wadud and White (2000), Samuel (2013) and Okoye (2007) employed the translog SFA for estimating the technical efficiency (TE), allocative efficiency (AE), and economic efficiency (EE) of rice production.

This paper extends on previous studies in applying SFA investigates of rice farmers in Myanmar (Kyi and Oppen, 2001; Myint and Kyi, 2005). The earlier papers mainly focused on investigating the output-oriented technical efficiency. In this analysis, we employ the input-oriented approach to measure efficiency and extend our analysis to allocative and economic efficiencies. Besides, the role of various farm-related factors in productive efficiency which was not considered in previous studies is also analyzed here.

Materials and methods

In order to estimate the production efficiency of rice production, a transcendental logarithmic (Trans-log) stochastic frontier functional form developed by Battese and Coelli (1995) was employed in this study. The general form of the production frontier model is

$$Y_i = f(X_j; \beta_j) + \varepsilon_i \tag{1}$$

where Y_i is output, X_i a vector of inputs and β_j a vector of parameters to be estimated. ε_i is the composite error term (v_i-u_i). v_i are random variables which assumed to be independently and identically distributed (i.i.d) $N(0, \sigma_v^2)$ due to factors outside the control of farmers (e.g., weathers, natural disasters, etc.). u_i is non-negative random variables associated with technical inefficiency in production which is assumed to be i.i.d by truncations (at zero) of the half-normal distribution ($u \sim \left|N(\mu, \sigma_u^2)\right|$) (Battese and Coelli, 1995). Next, we assume that the production function in equation (1) is self-dual and the dual cost frontier can be expressed in general form,

$$C_i = h(P_i, Y_i, \alpha) + \varepsilon_i \tag{2}$$

where C_i is the total cost, Y_i is a matrix of outputs, P_i is a vector of input prices, and α is a vector of cost parameters to be estimated. ε_i remain the same as previously defined.

Technical efficiency (TE) of the i^{th} farmer is defined by the ratio of the observed output (Y) to the corresponding frontier output (Y*) conditional on the levels of inputs used by the farm (Battese and Coelli 1988). Regarding this description, TE can be formulated by:

$$\begin{aligned} TE_i &= \frac{Y_i}{Y_i^*} = \frac{f(X_j, \beta_j)e^{v_i - u_i}}{f(X_j, \beta_j)e^{u_i}} \\ &= exp^{-u_i} \end{aligned} \tag{3}$$

The economic efficiency (EE), a value between zero and one, reveals the extent to which farmer succeeds in minimizing the cost of the given input and output prices. It can be formulated as follows:

$$EE_i = \frac{h(P_i, Y_i, \beta).\exp\{v_i\}}{c_i} = exp^{-u_i} \tag{4}$$

Allocative efficiency (AE) is defined as a product of TE and EE (Farrell, 1957). AE can be calculated from equation (3) and (4) as:

$$AE = \frac{EE}{TE} \tag{5}$$

Econometric specification

The translog stochastic frontier function for this study is defined as:

$$\begin{aligned} \ln Y_i &= \beta_0 + \sum_{j=1}^{6} \beta_i \ln X_{ji} \\ &+ \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n} \beta_{ij} \ln X_i \ln X_j + v_i - u_i \end{aligned} \tag{6}$$

where ln represents the natural logarithm; Y_i is rice output (in kg), X_i's inputs (land, seed fertilizer, pesticide, labor, m achinery). β's represents the input coefficients for the resources used in production while u_i and v_i are defined earlier. The maximum likelihood estimation of equation (6) provides for β, γ and σ_v^2, where β is a vector of unknown parameters, $\sigma^2 = \sigma_v^2 + \sigma_u^2$ and $\gamma = \sigma_u^2/\sigma_v^2$. An alternative representation of stochastic production frontiers of producers, cost function, is formulated as follows:

$$\ln C_i = \beta_0 + \beta_y \ln Y_i + \sum_{i=1}^n \beta_i \ln P_j + \frac{1}{2}\beta_{yy}[l\,n\,Y_i]^2 + \frac{1}{2}\sum_{i=1}^n \sum_{j=1}^n \alpha_{ij} \ln P_i \ln P_j + \sum_i \delta_{iy} \ln P_i \ln Y_i + v_i - u_i \tag{7}$$

Assuming a cost function is linearly homogenous in input prices, the symmetric restrictions require that $\beta_{ij}=\beta_{kj}$ must satisfy the following additional parameter restrictions such that:

$$\sum_i \beta_i = 1, \sum_i r_{ij} = 0, \sum_k \delta_{ij} = 0 \tag{8}$$

Therefore, the easiest way to handle such restrictions on the parameters of the cost function is to normalize the total cost and other input prices, using one input price. Schmidt and Knox Lovell (1979) investigated that it makes no difference either economically or statistically, which input price is used to normalize the equation. Thus, assuming a linear homogenous set of input prices, equation 7 is formulated as a normalized log-linear translog cost functional form:

$$\ln\left[\frac{C_i}{P_4}\right] = \beta_0 + \beta_y l\,n\,Y_i + \sum_{i=1}^n \beta_i \ln\left[\frac{P_j}{P_4}\right] + \frac{1}{2}\beta_{yy}[l\,n\,Y_i]^2 + \frac{1}{2}\sum_{i=1}^n \alpha_{ij} \ln\left[\frac{P_i}{P_4}\right] \cdot \ln\left[\frac{P_j}{P_4}\right] + \sum_i \delta_{iy} \ln\left[\frac{P_i}{P_4}\right] \cdot \ln Y_i \tag{9}$$

where ln represents the natural logarithm, C_i represents total input cost, P_{ij} is the input price and Y_i is output adjusted for statistical noise. The inefficiency model is estimated from the equation shown as below;

$$\mu_i = \delta_0 + \sum_{n=1}^{9} \delta_n Z_{ni} \tag{10}$$

where Z_i are farm-specific variables that may cause inefficiency described in Table 1 and δ_i's are unknown parameters to be estimated.

Specification of hypothesis

Three common hypotheses are often tested in the estimation of a stochastic frontier model. These are (1) the proper production functional form (i.e. whether the Cobb-Douglas or the translog functional form is the more appropriate form for the model), (2) whether or not the TE effects term u_i existing in the model, and (3) whether or not the socioeconomic variables do identify the TE effects term u_i. The three hypotheses are denoted mathematically as below:

$$H_0 : \beta_i = \alpha_{ij} = 0 \tag{11}$$

$$H_0 : \gamma = \gamma_0 = \ldots = \gamma_i = \delta = 0 \tag{12}$$

$$H_0 : \delta_1 = \delta_2 = \ldots = \delta_9 = 0 \tag{13}$$

Table 1. Summary statistics of the variables used in Ayeyarwaddy, Myanmar (2019).

Variables	Description	Mean	Standard deviation	Minimum	Maximum
Output and Inputs					
Yield	Rice yield ($kg \cdot ac^{-1}$)	1,681.922	505.159	625.800	2,920.400
Land	Total cultivated area (ac)	11.913	15.021	1.500	200.000
Seed	Seed utilization ($kg \cdot ac^{-1}$)	36.781	13.783	10.430	83.440
Fertilizer	Fertilizer utilization ($kg \cdot ac^{-1}$)	130.269	47.845	25.000	325.000
Pesticides	Pesticides usage ($L \cdot ac^{-1}$)	1.241	1.341	0.075	8.500
Labor	Total labor ($man\text{-}days \cdot ac^{-1}$)	41.587	30.161	6.000	164.000
Machine	Machinery utilization ($days \cdot ac^{-1}$)	2.851	1.164	1.000	8.750
Price of input					
Land	Price of land ($US\$ \cdot ac^{-1}$)	3,760.290	533.708	2,142.857	5,000.000
Seed	Price of seed ($US\$ \cdot kg^{-1}$)	0.281	0.079	0.171	1.027
Fertilizer	Price of fertilizer ($US\$ \cdot kg^{-1}$)	0.229	0.085	0.019	1.023
Pesticides	Price of pesticides ($US\$ \cdot L^{-1}$)	15.592	12.428	0.643	50.000
Labor	Wage of labor ($US\$ \cdot person^{-1} \cdot day^{-1}$)	3.845	0.538	2.857	7.143
Machine	Charge for machinery ($US\$ \cdot day^{-1}$)	16.122	4.596	6.731	35.714
Socio-economic variables					
Age	Age of respondent (year)	50.000	12.000	20.000	89.000
Family size	Number	5.000	1.690	1.000	15.000
Education	Respondents attained formal education (year)	4.714	2.880	0.000	15.000
Experience	Respondents' experience in rice cultivation (year)	26.000	13.840	2.000	74.000
Variety used	1 if respondent use improved variety, 0 otherwise	0.793	0.406	0.000	1.000
Extension	1 if farmers has contact with extension staffs, 0 otherwise	0.451	0.490	0.000	1.000
Training	1 if farmers receive agricultural training program, 0 otherwise	0.387	0.488	0.000	1.000
Off-farm	1 if farmers has an occupation other than farming, 0 otherwise	0.556	0.498	0.000	1.000

where β_{ij} are the squared values and interaction terms of the coefficients of inputs and the variables in equations 12 and 13 are defined earlier. These null hypotheses can be tested using the generalized likelihood-ratio statistic, λ, given by:

$$\lambda = -2[\ln\{L(H_0)\} - \ln\{L(H_1)\}] \tag{14}$$

where $L(H_0)$ and $L(H_1)$ denote the values of the likelihood function under the null (H_0) and alternative(H_1)hypotheses, respectively. If the given null hypothesis is true, λ has approximately χ^2 – distribution when the null hypothesis involves $\gamma = 0$ (Battese and Coelli, 1995).

Sampling and data collection method

The study area is growing not only the indigenous rice varieties but also the improved high yielding varieties. Among these varieties, the data for this study were collected from 300 rice farmers who grew *Sin Thu Kha* variety, one of the improved rice varieties. Data was collected using a structured questionnaire, rice yield, inputs used in the production process (land, seed, fertilizer, pesticides, labor and machinery) and the socio-economic farm-specific characteristics. These included farmer's age, household size, education level, farming experience, farm size, variety used, contact with extension agents, receiving agricultural training and off-farm activity. The variables used in this analysis were summarized by descriptive statistics analysis in Table 1.

The mean value of rice yield and farm size were 1681.92 kg per acre and 11.913 acres. On average, the seed rate, fertilizer and pesticide application used in rice cultivation per acre was 36.78 kg, 130.27 kg and 1.241 L. The average human labor including both family and hired labors 41.587 man-days per acre were applied on rice production. The machinery usage for land preparation, harvesting, and threshing were 2.851 days per acre.

In terms of input prices to compute the cost efficiency, land price was estimated at a mean of US$ 3760.29 per acre. The unit cost of seed and fertilizer were 0.28 US$ and 0.23 US$ per kilogram on average respectively. The mean price of pesticides was 15.59 US$·$L^{-1}$. The labor wage rate was 3.85 US$ per person. The machinery was valued at 16.12 US$ per day.

The mean value of the age is 50 years and the household size was five persons on average. The average education level was around 5 years indicating that most of the farmers had taken on primary education. Farmers had much experience in rice cultivation with a mean value of 26 years. Most of the farmers utilized the high yielding rice variety that it indicates about 0.793 levels of the variety of dummy variables. Out of the total sample household heads, only 45% have contacted with extension staff while 55% of them were not able to contact the extension staff. Training variables of 0.387 express that there was not enough agricultural training in this study area. Off-farm income dummy variables showed that nearly 56% of the farmers had other off-farm income activities whereas 44% of the farm families had no off-farm income activities in this sample area.

Results and discussions

Hypothesis testing

As indicated in the specification of hypotheses of Table 2, the study attempted to test three hypotheses. The first hypothesis was that the Cobb-Douglas functional form was an appropriate representation of the data, given the specification of the translog functional form. The second was that there were no inefficiency effects in our model. That is to say that the

Table 2. Hypothesis tests for appropriate functional form and statistical assumption.

Null hypotheses	LR	df	p-value	χ^2 -Critical value	Decision
Test (1)					
H_0: $\beta_i = \alpha_{ij} = 0$	20.140	1	0.000	6.631	Reject H_0
Test (2)					
H_0: $\gamma = \gamma_0 = ... = \gamma_j = \delta = 0$	40.300	21	0.000	32.671	Reject H_0
Test (3)					
H_0: $\delta_1 = \delta_2 = \ldots = \delta_9 = 0$	37.760	5	0.014	15.072	Reject H_0

Critical values are 1% significant level obtaining from Kodde and Palm's Table 1 (1986).
LR, log likelihood; df, degree of freedom.

inefficiency term u_i is absent and that the model is an ordinary average response model with v_i as the only error term. The last test expresses that the variables in the inefficiency effects model (socio-economic indicators) do not explain the inefficiency term u_i.

From Table 3 below all the three null hypotheses are rejected, implying (1) the translog functional form is a better representation of the data, (2) the presence of the inefficiency term u_i and (3) the explanatory variables determine u_i respectively.

Table 3. Maximum likelihood (ML) estimates of translog stochastic frontier production model.

Variables	Parameter	Coefficient	Standard error	t-ratio
Constant	β_0	0.951	2.840	0.330
ℓn land	β_1	0.516*	0.285	-1.810
ℓn seed	β_2	2.028***	0.708	2.860
ℓn fertilizer	β_3	0.837	0.769	1.090
ℓn pesticides	β_4	-0.559 **	0.272	-2.060
ℓn labor	β_5	0.327	0.470	0.690
ℓn machine	β_6	0.285	0.599	0.480
0.5 [ℓn land]^2	β_{11}	0.029	0.031	0.960
0.5 [ℓn seed]^2	β_{22}	-0.286**	0.148	-1.930
0.5 [ℓn fertilizer]^2	β_{33}	-0.174	0.135	-1.290
0.5 [ℓn pesticides]^2	β_{44}	0.048 *	0.028	1.720
0.5 [ℓn labor]^2	β_{55}	-0.016	0.061	-0.260
0.5 [ℓn machine]^2	β_{66}	-0.089	0.137	-0.660
[ℓn land × ℓn seed]	β_{12}	-0.041	0.058	-0.710
[ℓn land × ℓn fertilizer]	β_{13}	0.149***	0.053	2.820
[ℓn land × ℓn pesticide]	β_{14}	0.003	0.019	0.130
[ℓn land × ℓn labor]	β_{15}	-0.021	0.029	-0.720
[ℓn land × ℓn machine]	β_{16}	-0.067	0.050	-1.340
[ℓn seed × ℓn fertilizer]	β_{23}	-0.071	0.093	-0.760
[ℓn seed × ℓn pesticide]	β_{24}	0.116 ***	0.045	2.580
[ℓn seed x ℓn labor]	β_{25}	-0.100	0.072	-1.390
[ℓn seed x ℓn machine]	β_{26}	-0.132	0.088	-1.500
[ℓn fertilizer x ℓn pesticide]	β_{34}	0.065	0.042	1.560
[ℓn fertilizer x ℓn labor]	β_{35}	0.032	0.065	0.500
[ℓn fertilizer x ℓn machine]	β_{36}	0.097	0.076	1.270
[ℓn pesticide x ℓn labor]	β_{45}	-0.006	0.029	-0.200
[ℓn pesticide x ℓn machine]	β_{46}	-0.102***	0.039	-2.540
[ℓn labor x ℓn machine]	β_{56}	0.025	0.067	0.370
Variance parameter				
Sigma square	σ^2	0.149***	0.019	
Gamma	γ	0.892***		
Log-likelihood function		-3.438		

*** p < 0.01, ** p < 0.05, * p < 0.1.

Estimation of technical efficiency

The maximum likelihood (ML) estimates of parameters in the stochastic frontier defined by equation (6) are presented in Table 3. The first term variables of land, seed and pesticide were significant at 10, 1, and 5% respectively. The farmers who cultivate more land have the ability to increase rice output faster than the farmers with low land size under cultivation. However, pesticide utilization had a negative sign, meaning that increasing this variable decreased output.

The squared values of seed and pesticide usage also were significant, but seed utilization has a negative sign. Pesticide usage maintained a positive sign. The squared values of the inputs assist us to recognize the effect on output for the continuous usage of the inputs. In here, β_2 is positive but β_{22} is negative, it can be mentioned that at the initial stage, increasing the quantity of seed will lead to improved rice yield but later the quantity must be reduced for output.

The interaction parameters, β_{13}, β_{24} and $\beta_{46,}$ were significant which express us the complementarity or substitutability of the variables in Table 3. A positive or negative sign denotes that the two variables are complementary or substitutive. This means that land is complementary to fertilizer and seed is also complementary to pesticides while pesticide is the substitute for machinery.

The sigma squared (0.149) is significantly different from zero indicating a good fit and correctness of half-normal distribution assumption in Table 3. The gamma value (γ) is 0.892, proving the fact that high level of inefficiencies exists among farmers. This implied that 89.2% of the variation of rice yield was due to differences in technical inefficiencies among farmers and is highly significant at 1% level. If technical inefficiencies among farmers are minimized, rice output can be optimized.

Estimation of economic efficiency

Table 4 shows the maximum likelihood estimates of the cost frontier for rice production in Myanmar. The first term variables of land price had a positive sign and highly significant at 1% level. This implies that increasing the land prices by 1% would increase the total cost of production by 0.701.

The own-price elasticity of land and labor cost was significant with an appropriate negative sign, indicating that a decline in the cost of land and labor will lead to a decline in total production cost. The high value of labor coefficients indicates the importance of this variable in the cost structure of the farmers. Similarly, the cross-price elasticity between seed and labor, labor and machine were found positively significant at 10% level showing a direct relationship with total cost. And then, the coefficients for the interaction terms between seeds and machine, fertilizer and machine had an indirect relationship with total cost and statistically significant at 10% level.

The sigma (σ^2 = 0.49) and the gamma (γ = 0.336) were quite significant at 10% level. The significant value of the sigma square (σ^2) indicate the goodness of fit and correctness of the specified assumption of the composite error terms distribution. The estimated value of 0.336 means that 33.6 percent of the total variation in rice yield is due to economic inefficiency.

Frequency distribution of technical, allocative and economic efficiency for rice production

Table 5 shows technical, allocative and economic efficiency estimates of rice farmers. The study reveals that TE indices range from 35.08 percent to 95.69 percent with a mean of 76.11 percent. The study also suggests that for achieving more technical efficiency, the farmer could realize about 23.89% (1 - [76.11/100]) cost savings while the least technically efficient

Table 4. Maximum likelihood (MLE) estimates of translog stochastic frontier cost model.

Variables	Parameter	Coefficient	Standard error	t-ratio
Constant	β_0	25.772	15.991	1.610
ℓn land price	β_1	0.708**	0.086	8.150
ℓn seed price	β_2	3.560	4.695	0.760
ℓn fertilizer price	β_3	1.161	3.655	0.320
ℓn wage rate	β_4	-8.854	5.795	-1.530
ℓn machine fee	β_5	0.429	4.653	0.090
ℓn yield	β_6	-4.529	4.595	-0.990
0.5 [ℓn land price]^2	β_{11}	-0.060*	0.043	-1.770
0.5 [ℓn seed price]^2	β_{22}	-0.781	0.722	-1.050
0.5 [ℓn fertilizer price]^2	β_{33}	0.081	0.177	0.480
0.5 [ℓn wage rate]^2	β_{44}	-4.952***	1.552	-3.180
0.5 [ℓn machine fee]^2	β_{55}	-0.088	0.435	-0.200
0.5 [ℓn yield]^2	β_{66}	0.367	0.634	0.580
[ℓn land price × ℓn seed price]	β_{12}	0.042	1.105	0.040
[ℓn land price × ℓn fertilizer price]	β_{13}	0.059	0.693	0.090
[ℓn land price × ℓn wage rate]	β_{14}	1.242	1.095	1.130
[ℓn land price × ℓn machine fee]	β_{15}	-0.376	0.872	-0.430
[ℓn land price × ℓn yield]	β_{16}	0.217	0.522	0.420
[ℓn seed price × ℓn fertilizer price]	β_{23}	0.105	0.346	0.300
[ℓn seed price × ℓn wage rate]	β_{24}	1.582*	0.857	1.850
[ℓn seed price × ℓn machine fee]	β_{25}	-1.027*	0.549	-1.870
[ℓn seed price × ℓn yield]	β_{26}	-0.538	0.655	-0.820
[ℓn fertilizer price × ℓn wage rate]	β_{34}	0.234	0.668	0.350
[ℓn fertilizer price × ℓn machine]	β_{35}	-0.493*	0.284	-1.730
[ℓn fertilizer price × ℓn yield]	β_{36}	-0.039	0.362	-0.110
[ℓn wage rate × ℓn machine fee]	β_{45}	1.641*	0.886	1.850
[ℓn wage rate × ℓn yield]	β_{46}	0.485	0.628	0.770
[ℓn machine fee × ℓn yield]	β_{56}	-0.262	0.470	-0.560
Variance parameter				
Sigma square	σ^2	0.487*	0.090	
Gamma	γ	0.336		
Log-likelihood function		-223.159		

*** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table 5. Frequency distribution of efficiency estimates from stochastic frontier model.

Efficiency	Mean value	Minimum	Maximum	Std. dev.
TE	76.114	35.076	95.698	0.136
AE	47.853	1.324	100.000	0.426
EE	34.151	1.088	99.985	0.265

TE, technical efficiency; AE, allocative efficiency; EE, economic efficiency; Std. dev., standard deviation.

farmers will have about 64.92% (1 - [35.08/100]) cost savings to become the most efficient farmer.

The mean allocative efficiency was 47.85%, ranging from 1.32 to 100. The result presented that the average rice farmer would enjoy cost saving of about 52.15% (1 - [47.85/100]) if he or she attains the most efficient level among the respondents. The average cost efficiency score was 34.15%, ranging from 1.09 to 99.99. The farmers will need to reduce production costs by 65.85% and will still be capable of attaining the current level of rice output. The rice farmers in the study area were economically inefficient as a result of allocative inefficiency.

Factors affecting efficiency estimates among rice farmers in Myanmar

The efficiency model in Table 6 gives some observations on factors affecting production efficiency. Results have exposed that age variable has a negatively significant impact on TE, AE and EE at 10% level which implies that younger farmers are more efficient than older ones. The result is consistent with the study of Hussain (1989) who implied that older farmers are less likely to have contact with extension agents and are less willing to adopt new practices and modern inputs.

The coefficient for household size has a negatively significant effect on EE at 5% level. This described that large family size increase the labor availability though large family sizes may not guarantee to improve efficiency since family labor which involves mostly children of school age are always in school. Education is positively significant on TE at 10% level. This indicates that educated farmers improve their technical performance through access to information and good farm planning. Experience has a positive significant effect on AE. This suggests that an increase in the duration of the farmer's involvement in rice production increases their productivity. This suggests that management skill aspects, such as the optimal timing of operations, are important

Farm size had a negative coefficient and was highly significant on AE and EE at 1% level. This implies that farmers with small farm holdings are allocative and economically efficient. This consistent with Van Zyl (1995) who reported that commercial farms could become significantly more efficient if they become smaller. Variety had a positive significance on TE and EE at 5% and 10%. The farmers who grow improved rice variety are more efficient than those who do not. This

Table 6. Determinants of technical, allocative and economic efficiency in rice production.

Variables	Para-meter	TE		AE		EE	
		Coefficient	Std. dev.	Coefficient	Std. dev.	Coefficient	Std. dev.
Constant	δ_0	0.755***	0.042	0.859***	0.134	0.635***	0.079
Age	δ_1	-0.002*	0.001	-0.003*	0.003	-0.001**	0.002
HH size	δ_2	0.001	0.004	-0.019	0.012	-0.015**	0.007
Education	δ_3	0.002**	0.002	0.002	0.007	0.001	0.004
Experience	δ_4	0.001	0.001	0.004**	0.002	-0.002	0.001
Farm size	δ_5	-0.001	0.004	-0.021***	0.002	-0.015***	0.001
Variety	δ_6	0.026**	0.016	0.066	0.051	0.034*	0.031
Extension	δ_7	0.005	0.013	-0.045	0.041	-0.028	0.024
Training	δ_8	0.168***	0.013	0.090**	0.043	0.036	0.024
Off-farm	δ_9	-0.036***	0.014	0.059	0.044	0.008	0.026

Technical efficiency (TE) index, allocative efficiency (AE) index and economic efficiency (EE) index are used as dependent variables.
Std. dev., standard deviation; HH, household.
***, **, and * are statistically significant at 1, 5, and 10% respectively.

shows that the use of high yield varieties are necessary conditions This result is in line with the findings of Galawat (2012) who revealed that high yielding varieties had a positively significant impact on TE and EE of rice production in Brunei Darussalam.

Agricultural training had a positively significant interaction on TE and AE at 1% and 5% level. The result implies that rice farmers can increase productivity by conducting practical, effective and efficient training programs. In this study, off-farm income is recognized to decline technical efficiency. This means that managerial input may be taken away from agricultural activities with increased contribution of the educated in non-farm activities, which leads to lower efficiency. Similarly, Abdulai and Huffman (1998) found higher inefficiency of production with the involvement of households in non-farm activities.

Conclusions

This paper has investigated into the level of technical, allocative and economic efficiency of 300 rice farmers and also identify socio-economic and farm-specific factors that influence TE, AE and EE in rice farmers in Myanmar. Maximum likelihood techniques were used to estimate stochastic translog production frontier, which was then used to derive its corresponding dual cost frontier. In terms of methodology, the translog specification of the model performed better than the Cobb-Douglas specification. The inputs that were significant in influencing output were land, seed and pesticide. The analysis reveals the mean levels of technical, allocative and economic efficiency scores equal to 76.11, 47.85, and 34.15% respectively. The average technical efficiency of 76 percent reveals that there is considerable room for improvement in rice productivity among farmers to achieve maximum efficiency.

The relationship between TE, AE and EE and various attributes of the farm and farm characteristics were investigated in a second step analysis. Results showed that younger farmers were most likely to operate farming activities efficiently. Education is an important factor, indicating that education increases people's ability to recognize issues related to the adoption of modern technologies. Small farm farmers are more allocatively and economically efficient than farmers with large farm in Myanmar. Farmer should operate on medium-sized farms to compensate for the loss of cost on operating in big farms.

The rice seed being the fundamental input in production, its high quality forms the basis of high farm efficiency and productivity. The input seeds currently utilized by most farmers are impure because they produce the seeds on their owned farms using traditional methods. Growing high-yielding variety would help to improve farmers' profit. Strengthening and establishing both formal and informal type of framers' training centers, technical and vocational schools, and agricultural training would reduce both allocative and economic inefficiencies.

Our findings suggest for the important policy implications. The respective institution needs to give an incentive to people of productive age to work in the agricultural farm to improve rice productivity. Also, the government could play a responsibility in ensuring that pure and high-quality seeds are available to rice farmers. Moreover, the farmer field schools program, supported by different development agencies cooperating with the Department of Agriculture, may be rigorously implemented to help farmers improve their analytical and decision-making skills in rice production. In addition, scaling up/out of those efficient farmers' experience via training, field visits and field demonstrations could be the right steps for enhancing the farmers' awareness in the adoption of advanced farming practices positively towards efficient rice production. Farm technology should be considered as an appropriate step for improving efficiency and boosting output. Farm mechanization will potentially support to decrease in the cost of agricultural labor that is a major obstacle to both technical and cost efficiencies of rice farmers. Thus, it is imperative for the government to continue more emphasis on the mechanized farming system than the current conditions to drive agricultural growth and productivity.

Conflict of Interests

No potential conflict of interest relevant to this article was reported.

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