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# FARMERS' EDUCATION, MODERN TECHNOLOGY AND TECHNICAL EFFICIENCY OF RICE GROWERS

# Uttam Kumar Dev Mahabub Hossain

#### **ABSTARCT**

The study develops a model to estimate the farm specific technical efficiency of rice farmers under heterogeneous human resources and technological environment. Based on farm level data, collected from Bangladesh, it validates the model and estimates the contribution of farmers' education, and modern technology on farm specific technical efficiency in rice production. The study concludes that, under heterogeneous human resources and technological condition, farm specific technical efficiency can be assessed either through incorporation of farmers' education and technology directly into the production function or through a two stage analysis -estimating farm specific technical efficiencies first and then regressing the technical efficiencies to different explanatory variables including farmers' education and technology index.

#### 1. INTRODUCTION

It is well recognized that education has a positive effect on the adoption of new technologies and efficient organization of production. Farmer education increases the information acquisition ability and adjustment ability of the farmer, thereby providing awareness regarding opportunities for productive employment and incomes and rational expectation for decision making. It is then possible for the farmer to decide to increase output through efficient input use. Technical efficiency (TE) is used as a measure of a farm's ability to produce maximum output from a given set of inputs and production technology. Therefore, we hypothesize that an educated farmer would be better able to increase technical efficiency in total rice production from his given stock of resources than his illiterate counterpart.

Existing studies analyze technical efficiency of crops for a particular season under homogeneous agroecosystems such as irrigated, non-irrigated MV, local, wet season, dry season etc. (Huang and Bagi, 1984; Kalirajan and Shand, 1985; Kalirajan, 1981, 1984; Lingard, Castillo and Jayasuriya, 1983; Kalirajan and Flinn, 1983; Ekayanake, 1987; Kalirajan and Shand, 1986; Shapiro and Muller, 1977; Rawlins, 1985; Phillips and Marble, 1986; Bravo-Ureta and Evenson, 1994; Taylor and Shonkwiler, 1986). These studies are unable to estimate technical efficiencies on a whole farm basis and under heterogeneous human resource level and

This paper is derived from the first author's Ph. D. thesis submitted to the University of the Philippines at Los Banos. The authors are Scientific Officer, Agricultural Economics Division, Bangladesh Rice Research Institute, Gazipur-1701; and Economist and Head, Social Sciences Division, IRRI, P.O. Box 933, 1089 Manila, Philippines, respectively.

technological condition (combination of both local and MV rice). To fill this lacuna of methodology and empirical analysis, we need to develop a model and estimate technical efficiency on a whole farm basis.

Technical efficiency estimation on a whole farm basis has some empirical problems. The output potential of different farms are not same due to the differences in the technology level and level of human resources or knowledge stock of the farm. Farmers cultivate both modern and local varieties. The potential yield of local and MVs are different. Therefore, unless we can develop an analytical tool which is capable to take these into consideration, technical efficiency estimation on a whole farm basis is not possible.

Endogenous growth models (Romer 1986, 1990; Lucas 1988) have given more emphasis on the knowledge stock or human capital and show that the material effect of knowledge is far beyond the residual growth, Romer (1990) stresses to take four factors of production into account: capital, unskilled labor, human capital (for instance, years of schooling) and an index of the level of technology. This theoretical underpinning gives us an opportunity to include knowledge or farmers' education and technology as factors of production into the production function. Hence, it is possible to write the rice production function as follows:

$$Y = F(K, L, S, T) \tag{1}$$

where Y is the quantity of total rice output; K, L, and S represent quantities of physical capital, labor, and human capital, respectively; and T is an index of the level of technology. We may also treat Y, K, and S as a vector of output, capital input, and farmers' education.

This paper tries to develop and validate an econometric model to estimate farm specific technical efficiency in rice production on a whole farm basis under heterogeneous human resources and technological conditions. Section 2 discusses the analytical framework while the data and empirical procedures are discussed in the third section. Section 4 deals with empirical results and conclusions are placed in the last section.

## 2. THE DATA AND ANALYTICAL FRAMEWORK

The data used in this study were drawn from a sample survey of farm households under the Ganges-Kobodak (GK) Irrigation project. The Farm Management Division of the GK project conducts farm survey on a regular basis to estimate cost of production in crop cultivation to assess the projects impact on the income of the farmers. The data were not available in computer usable electronic file. However, we were given access to the filled in questionnaires that were kept in store. We processed those data for our analysis for two periods, 1985-86 and 1990-91. The analysis is confined to the farmers under Phase 2 of the GK project. After careful scrutiny regarding inconsistency and incomplete information, we decided to use the information for 411 farmers in 1985-86, and 825 farmers in 1990-91. The data were collected by the extension overseers of the Ganges-Kobodak Irrigation Project authority. They prepared

a list of farmers of different villages and from that list they randomly interviewed a subsample of farmers.

Following Aigner et. al. (1977), we used a stochastic production frontier. The key feature of the stochastic production frontier is that the disturbance term is composed of two parts, a symmetric and a one-sided component. The symmetric component captures the random effects outside of the control of the decision-maker including the statistical noise contained in every empirical relationship particularly those based on cross-section household survey data. The one-sided component captures deviations from the frontier due to inefficiency. The biggest advantage of the stochastic production frontier model is the introduction of a disturbance term representing noise, measurement error, and exogenous shocks beyond the control of the production unit in addition to the efficiency component. Hence TE measures obtained from stochastic frontiers are expected to reflect the true ability of the farmer given the resources. Estimation technique of a stochastic production frontier is discussed below.

Let us assume that the farm production frontier can be written as

$$Y_i = f(X_i, \beta) \tag{2}$$

where  $Y_i$  is the maximum rice output obtainable from  $X_i$ , a vector of (non-stochastic) input quantities and  $\beta$  is a vector of parameters. Therefore, the stochastic production frontier can be written as

$$Y = f(X_i, \beta) + \epsilon \tag{3}$$

where

$$\epsilon = v - u$$
 (4

is the composed error term (Aigner, Lovell and Schmidt, 1977; Meusen and van den Broeck, 1977). The two components v and u are assumed to be independent of each other, where v is the two-sided, normally distributed random error  $(v \sim N \ (0, \sigma_v))$ , and u is the one-sided efficiency component with a half-normal distribution  $(u \sim |N \ (0, \sigma_v^2)|)$ . The Maximum likelihood estimation of equation (2) yields estimators for  $\beta$  and lambda, where  $\beta$  is as defined earlier, lambda =  $\sigma_u/\sigma_v$  and  $\sigma^2 = \sigma_u^2 + \sigma_v^2$ .

Jondrow *et al.* (1982) have shown that the assumptions made on the statistical distributions of v and u, as mentioned above, make it possible to calculate the conditional mean of  $u_i$  and  $e_i$  as:

$$E\left(u_{j} \mid \epsilon_{j}\right) = \sigma^{*} \left[\frac{f^{*}(\epsilon_{j} \lambda / \sigma)}{1 - F^{*}(\epsilon_{j} \lambda / \sigma)} - \frac{\epsilon_{j} \lambda}{\sigma}\right]$$

$$(5)$$

where  $F^*$  and  $f^*$  are, respectively, the standard normal density and distribution functions, evaluated at  $\in_j \lambda/\sigma$ , and  $\sigma 2 = \sigma^2_u \sigma^2_v / \sigma^2$ . Therefore, equations (3) and (4) provide estimates for u and v after replacing  $\in$ ,  $\sigma$ , and by their estimates. If v is now substracted from both sides of equation (3), we obtain:

$$Y^* = f(X_i; \beta) - u = Y - v \tag{5}$$

where y\* is the farm's observed output adjusted for the statistical noise captured by v.

In closing this section, it is useful to point out that an important issue in stochastic frontier model is the distributional assumptions made for one-sided error. Much of the literature to date, including this paper, has followed the half-normal distribution, as originally proposed by Aigner, Lovell and Schmidt (1977), despite the fact that more flexible distributions are available. One of the few papers that have examined the sensitivity of the efficiency results to distributional assumptions is published recently by Greene (1990) where he introduced a stochastic frontier specification that incorporates the Gamma distribution. After comparing several specifications, Greene (1990) concluded that, for his data, efficiency levels were essentially the same for the half-normal, truncated normal and exponential distributions while the Gamma model yielded higher efficiency. In a review of new developments in frontier function methodology, Bauer (1990) argued that additional empirical as well as theoretical work is needed to arrive at a better understanding of the effects that alternative distributional assumptions have on efficiency.

We used equation (6) and equation (7) to estimate the contribution of farmers' education, technology and other factors of production to total rice output.

$$InY_{i} = \alpha o + \alpha_{1} lnX_{1} + \alpha_{2} LnX_{2} + \alpha_{3} LnX_{3}$$
(6)

$$In Y_i = \alpha_0 + \alpha_1 \ln X_1 + \alpha_2 \ln X_2$$

$$+ \alpha_3 LnX_3 + \alpha_4 EDN + \alpha_T TECH$$
 (7)

where: In is the natural log of the variables,  $Y_i$  is total rice output of the farm (kg),  $X_1$  is total rice area (acres). X2 is total pre-harvest labor used for rice production (man days), we considered total labor used in pre-harvest operations in rice production. Production economists argue that labor used for harvest and postharvest operations is the outcome of production and does not contribute to output. Therefore, labor used for land preparation, transplanting, weeding, fertilizer and insecticide application, water management, and pesticide application are included as labor input and it is expressed in man days. The data includes labor contributed by both family and hired workers. X3 is total cost (Taka) of inputs (seed, fertilizer, pesticides and bullock power) used for rice production is treated as working capital. Seed, fertilizer, draft power, and irrigation are complementary to each other, not substitues. Therefore, we took these factors together rather than separate. Ideally, we should include the cost of irrigation also as working capital, But farmers under the GK project rarely pay for the publicly managed irrigation system. The water is charged at a flat rate independent of the intensity of irrigation. Though there is a provision for irrigation charges, this was not realized. For this reason, we have not included this as working capital. EDN is education level of the farm operator (years). As an index of the level of technology (TECH), we used proportion of MV rice to total cultivable area of the farm. For both aus and aman season, we calculated proportion of MV rice area to total cultivable area and added it together. That is,

$$TECH = \frac{MV \ AUS \ AREA}{TOTAL \ CULTIVABLE \ AREA} + \frac{MV \ AMAN \ AREA}{TOTAL \ CULTIVABLE \ AREA}$$

In addition, we tried to measure the technology level of the farm through proportion of irrigated rice area (PIRGA). PIRGA is measured as

$$PIRGA = \frac{IRRIGATED\ AUS\ AREA}{TOTAL\ CULTIVABLE\ AREA} + \frac{IRRIGATED\ AMAN\ AREA}{TOTAL\ CULTIVABLE\ AREA}$$

Using the LIMDEP computer package developed by Green (1991), we estimated the parameters of the production function (equation 6 and equation 7) and level of technical efficiency among the sample farms. To determine the effect of farmers' education and technology index on technical efficiency in rice production we used two approaches - direct approach and indirect approach. In the direct approach, we have run two models for estimating technical efficiency. In one model, we incorporated farmers' education and technological idex as inputs of rice production in addition to the traditional inputs (land, labor, capital) and estimated farm specific technical efficiency level. Technical efficiency estimates based on this model is mentioned as TE2. In the other model, we have not incorporated these two factors (farmers' education and technology index)- i. e., we have taken only the material inputs (land, labor, capital) and estimated farm specific technical efficiency. Technical efficiency estimates obtained from this model are mentioned as TE1. Therefore, TE1 indicates efficiency level based on traditional inputs only (land, labor, working capital) while TE2 indicates efficiency level based on all inputs including farmers' education and technology. In the indirect approach, TE1 is treated as farm specific technical efficiency; that is, technical efficiency estimates based on material inputs (land, labor, working capital) are treated as farm specific technical efficiency. Then we have run a regression analysis to determine the factors responsible for technical efficiency differences among farms. In the regression analysis, we have taken farmers' education and technology as explanatory variables.

#### Determinants of technical efficiency in rice production

To estimate the contribution of farmers' education and other factors to the technical efficiency in rice production we run an ordinary least square regression of the following form:

$$TE1 = f$$
 (EDN, TECH, PIRGA, FLOOD, DROUT

(8)

### FSIZE, PRNTA, AGE, FAMSZ, TIMEDUMMY)

Where: TE1 is the technical efficiency in rice production estimated for the traditional inputs (land, labor, working capital) i.e., using equation (6). FLOOD is proportion of flood-prone area proxied by the proportion of deep water rice and mixed *aus-aman* rice area to total rice area, DROUT is the proportion of drought prone area proxied by the proportion of rice area under broadcast *aus* rice area to total rice area, FAMSZ is family size (persons) and meas-ures

the subsistence pressure of the family, FSIZE is farm size (acre), PRNTA is proportion of rented in area. AGE is age of the farm operator (years), TIMEDUMMY is time dummy (if year = 1985 then 0 and if year = 1990 then 1). other variables are as mentioned earlier.

# 3. EMPIRICAL RESULTS

Table 1 shows the basic characteristics of the sample farms and the study area. Average farm size is 1.47 ha. Most of the farmers (91 percent) have less than 3 ha of farm size while only 9 percent farms has 3 ha and above farm size. Rate of MV adoption is higher (52 percent) in wet season compared to the dry season (37 percent). Extent of irrigation coverage in the wet season is also higher. In the wet season, 54 percent of the total cultivable area is under irrigation while in the dry season it is 47 percent. Fertilizer (NPK) use in rice during the dry and wet season are 187 and 98 kg/ha, respectively. Average yield of paddy is 3.6 ton/ha. Average family size is 6.9 persons. Average age of the farm operator and all adult male members are 47 and 33 years, respectively. Average years of schooling of the farm operators and all adult male members are 3.4 and 4.2 years, respectively.

Table 1. Basic characteristics of the sample farms, 1985/86 and 1990/91.

Description	Value	
No. of households	1,236	
Average farm size (ha)	1.47	
Percentage distribution of farms:		
Small (less than 1 ha)	43.6	
Medium (1 to less than 3 ha)	47.5	
Large (3 ha and above)	8.9	
Average paddy area (ha)	1.59	
Irrigated area as a percent of total cultivable area:		
Dry (Aus) season	46.52	
Wet (Aman) season	53.95	
MV paddy area as percent of total cultivable area:		
Dry (Aus) season	36.95	
Wet (Aman) season	51.72	
Fertilizer use (NPK/ha):		
Dry (Aus) season	187.47	
Wet (Aman) season	98.42	
Paddy yield (t/ha)	3.62	
Average family size (Persons)	6.91	
Age of the farm operator (years)	47.38	
Education level of the farm operator (years)	3.40	
Average age of all adult male members (years) <sup>a</sup>	33.14	
Average education level of all adult male members (years) <sup>a</sup>	4.19	

Note: a means above 10 years age.

The OLS and ML estimates of the production function analysis (equation 6 and equation 7) are presented in Table 2. Elasticity of rice output with respect to land  $(x_1)$  is 0.61.) It indicates that a hundred percent increase in rice area increases the total rice output by 61 percent. The elasticity of rice output with respect to preharvest labor  $(x_2)$  is 0.26, implying that a hundred percent increase in preharvest labor use increases the total rice output by 26 percent. The elasticity of rice output with respect to working capital  $(x_3)$  is 0.19, indicating that a hundred percent increase in working capital increases total rice output by 19 percent. Education level of the farm operator (EDN) has almost zero or insignificant effect. Technology index (TECH) has a high coefficient (0.35) and significant at 1 percent lavel of significance. It implies that 10 percent increase in MV area increases total rice production of the farm by 3.5 percent. Returns to scale in material inputs estimated through the sum of elasticities is 0.97, which implies that constant returns to scale prevail in material inputs. Returns to scale in all inputs including farmers' education and technology measured through the sum of individual elasticities is 1.32. This indicates that increasing returns to scale prevails when farmers' education and technology index are incorporated into the production function.

Table 2. Estimates of the rice production function, 1985/86 and 1990/91.

		OLS Estima	ates	MLE stimates			
Variable	, 1	. II	Ш	1	11 -	III .	
Constant	4.76**	5.80**	5.07**	5.74**	6.02**	5.6**	
	(29.295)	(40.419)	(33.93)	(38.791)	(44.257)	(38.174)	
In X <sub>1</sub>	0.61**	0.74**	0.67**	0.69**	0.74**	0.0*	
	(19.709)	(27.649)	(23.447)	(26.021)	(30.418)	(26.772)	
In X <sub>2</sub>	0.26**	0.16**	0.20**	0.21**	0.16**	0.20*	
	(9.339)	(6.840)	(8.244)	(8.915)	(7.497)	(8.70)	
In X <sub>3</sub>	0.19**	0.07**	0.15**	0.13**	0.07**	0.2*	
	(9.120)	(3.839)	(7.594)	(6.569)	(3.781)	(6.20)	
EDN	-	-0.001	-0.001		-0.00	-00.1	
		(-0.462)	(0.753)		(-0.281)	(0.508)	
TECH	-	0.35**		-	0.33**	- (0.500)	
		(22.936)				(21.536)	
PIRGA	-		0.22**	-	, <u>.</u> .	0*	
			(15.907)			(14.8)	
$\sigma_{u}/\sigma_{v}$	-	-	-	2.92**	1.17**	1.99*	
5 6 7				(11.694)	(6.631)	(10.338)	
$(\sigma_{\rm u}^2 + \sigma_{\rm v}^2)^{0.5}$		-	-	0.43**	0.30**	0.3*	
				(34.836)	(22.491)	(29.82)	
Adj. R <sup>2</sup>	0.92	0.95	0.94	-	,	(25.52)	
Log-L			•	-140.33	25.50	-59.68	

Note: Figures in the parentheses are asymptotic t-values.

<sup>\*\*</sup> indicates significant at 1 percent level of significance.

Table 3 shows the techincal efficiency in rice production among sample farms. In the direct approach, average level of technical efficiency in material inputs is 0.74. It increased to 0.84 when technology and farmers' education were considered as inputs into the production function. The absolute level of variability in technical efficiency among sample farms was reduced when we incorporate farmers' education and technology into the production function in contrast to technical efficiency estimates based on only material inputs. Relative variability of techical efficiency measured through the coefficient of variation was also reduced after the incorporation of farmers' education and technology into the production function. Since we found that farmers' education has no significant effect on technical efficiency in rice production, then it can be argued that technology index is the determining factor of technical efficiency differences among farms. Average technical efficiency level among farms is 84 percent, which implies that there is scope for 16 percent efficiency increase. Achieving the full potential will lead to some additional output.

Table 3. Technical efficiency estimates of the sample farms, 1985/86 and 1990/91.

VARIABLE	MEAN	STD. DEV.	CV (%)	
TE1	0.74	0.143	19.31	
TE2	0.84	0.066	7.83	

Note: TE1 - Technical efficiency estimates based on traditional inputs only.

TE2 - Technical efficiency estimates based on all inputs including farmers' education and technology.

Table 4 compares technical efficiency (TE) indices and role of farmers' education on TE from various studies using production frontier. It is observed from the table that our estimates are comparable to other studies. Banik (1994), based on farm survey data from 99 farms of Dhamrai, Bangladesh, found that the median level of technical efficiency in irrigated modern Boro rice cultivation is 0.82, which implies that under a homogeneous technological environment, most expected technical efficiency level is 0.82. Our estimated average efficiency level (0.84), when estimated including technology index, is comparable with Banik's estimates. And the advantage of our estimation technique is that it can be estimated and compared under heterogeneous technological environment rather than under the same technological environment. Technical efficiency can be estimated for whole farm basis rather than plot or parcel basis.

Using the indirect approach, determinants of technical efficiency (TE1) in rice production (only traditional inputs based efficiency) were estimated through the determinant analysis discussed in Section 2. Results of the determinant analysis (equation 8) are presented in Table 5. Education has no significant effect on technical efficiency. The underlying reason for insignificant effect of farmers education on technical efficiency can be explained by the non-

agriculture oriented education system of Bangladesh. To improve technical efficiency in farming through education Bangladesh need to expand agriculture oriented education system.

Table 4. Summary of frontier studies on technical efficiency and on role of education in attaining technical efficiency.

Source, locat- ion and year of	Crop	Sample	Method of	Average	Role of education
study		Size	Estimation	Inefficiency (%)	
Belbase & Gra-	Rice	537	Probabilistic,	16	Education had significant (10% level)
bowski, 1985 (Nepal)			COLS (CD)	33	negative effect on the level of inefficiency.
Phillips and Marble, 1985	Maize	1,548	COLS (CD)	53	Education had significant (10% level) negative effect on the level of inefficiency.
Kalirajan, 1981 (Tamil Nadu, India, 1978)	Rice	70	Stochastic frontier	53	Negative but significant effect of formal education on the level of ine-
Inuia, 1976)					fficiency, howe-ver, both knowledge and extension contact had significant (10% level) negative effect on the level of inefficiency.
Pradhan, 1994	Rice	307	Stochastic	FMIS-23	Positive but not significant on TE at
(Chitwan,			frontier (MLE)	GMIS-29	10% level of significance. Negative
Nepal)			Ф		and not significant on TE at 10%
Valiation and	Divi				level of significance.
Kalirajan and Flinn 1981 (Bulacan, Philippines)	Rice	54	Stochastic frontier	20	Formal education had insignificant negative effect on the level of inefficiency. However, extension contact had significant (10% level) negative contribution to the level of
W.1	D'	=0			inefficiency.
Kalirajan and Flinn 1983 (Bicol, Philip- pines) 1980	Rice	79	Stochasic frontier	50	Both extension contact and experience had significant negative effect on the level of inefficiency at 10% level of significance.
Lingard et al., 1983 (Central	Rice	32	Analysis of covariance	50	Formal education has significant negative contribution on the level of
Luzon, Philippines) 1970-79)			with firm spe- cific dummies (CD)		inefficiency ot 10% level of significance.
Flinn and Ali, 1986 (Punjab, Pakistan 1982)	Rice	120	Stochastic forntier	21	Education has significant negative contribution to the level of inefficiency at 10% level of significance.
Hossain, 1989 (NWFP, Pakistan)	Wheat	105	Stochastic frontier	31	Knowledge score has significant negative impact on the level of ine-fficiency at 5% level of significance.

Table 4. (Conted)

(2)						
Source, locat- ion and year of study	Crop	Sample Size	Method of Estimation	Average Inefficiency (%)	Role of education	
Banik, 1994 (Dhamrai, Bangladesh)	Boro rice	99	Stochastic Frontier	18	The study did not conduct any TE determinat analysis to see the contribution of education and other factors on TE, but it observed that farms with higher level of technical efficiency are primary educated and they have frequent contact with the	
Kumbhakar, Bisws and Bailey 1989 (Utah, USA)	Dairy farm	89	Stochastic Production Frontier		extension personnel.  Positive association between farmer education and Bailey, productive efficiency were found.	
Battese and Coelli 1994 (India, 1975/ 76-1984/85)	Rice		Stochastic Production Frontier (Panel data)	19	Farmers with greater years of schooling tend to be less inefficient.	

FMIS = Farmer managed irrigation system. GMIS = Government managed irrigation system.

LP = Linear programming, COLS = Correlated ordinary least squares, MLE = Maximum likelihood estimation, CD = Cobb-Douglas.

Technology index either measured through varietal technology adoption (TECH) or measured through proportion of irrigated area (PIRGA) showed significant positive contribution at 1 percent level of significance to technical efficiency of farm as indicated by high 't' values. Proneness to the flood and drought has significant negative effect on technical efficiency level. This implies that technical and environmental factors are important in determining technical efficiency in rice production.

Our estimated results show that farm size and tenurial status have insignificant negative effect on the level of technical efficiency. Banik (1994) also found that, in an irrigated and modern rice technological environment, farm size and tenurial status of land has no effect on technical efficiency.

Age of the farmer (AGE) has no significant effect on technical efficiency. This indicates that age of the farmers do not create any significant difference in technical efficiency.

Subsistence pressure (FAMSZ) has no significant effect on the level of technical efficiency. Time dummy has significant positive effect on technical efficiency indicating that efficiency had increased over time.

Thus our empirical analysis support the theoretical analysis that the direct way of measuring contribution of farmers' education and technology to rice output through production function provides same results as that of indirect way of measuring.

Table 5. Determinants of technical efficiency (based on traditional inputs only) in rice production, 1985/ 86 and 1990/91.

n 202	Estma	ites
Variable	1.4,	
Constant	0.732**	0.734**
	(40.935)	(39.458)
EDN	-0.001	-0.001
	(1.856)	(-1.745)
TECH	0.095** (9.025)	-
PIRGA	• ,	0.057**
		(7.658)
FLOOD	-0.144**	-0.191**
	(-2.975)	(- 4.070)
DROUT	-0.244**	-0.287**
	(-10.831)	(-13.043)
FSIZE	-0.001	-0.001
	(0.636)	(0.639)
PRNTA	-0.037	-0.055*
	(-1.295)	(-1.932)
ACE	-0.000	-0.000
	(-1.323)	(-1.633)
FAMSZ	-0.001	-0.001
	(0.808)	(0.824)
TIME DUMMY	-0.008	0.042**
	(-0.822)	(4.850)
Adj. R <sup>2</sup>	0.41	0.40

Not: Figures in the parentheses are asymptotic t-values.

# 5. CONCLUDING REMARKS

Farmers' education had no significant role on rice output and technical efficiency in rice production. Constant returns to scale prevails in the material inputs and increasing returns to scale prevails to all inputs when technology index and farmers' eduction are included. There are significant differences in technical efficiency among farms when we do not take into account the index of technology and the level of farmers' education used in the production process. Incorporation of these two factors into the production function reduces technical efficiency

<sup>\*\*</sup> indicates significant at 1 per cent level of significance.

<sup>\*</sup> indicates significant at 10 percent level of significance.

differences among rice farmers. Both the direct and indirect way of techincal efficiency estimation show that technology has significant positive contribution to technical efficiency in rice production while farmers' education has no significant contribution. This implies that our direct way of measuring the contribution of farmers' eduction and technology to rice output provides the same results as that of the indirect way of measuring (through efficiency determinant function).

#### Footnote

It should be noted that several years ago Greene (1980) introduced the Gamma distribution in the context of a deterministic frontier model.

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