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CROP-SPECIFIC PRODUCTIVITY AND EFFICIENCY OF BANGLADESH RICE CROPS AND DEVELOPMENT POLICY

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Abstract
The rice production of Bangladesh has been investigated using a Cobb-Douglas stochastic frontier production function which incorporated a model for the technical inefficiency effects. The farm level primary data which is used for this study has been collected by stratified random sampling technique. The per hectare production, cost, gross, net returns and benefit cost ratio were the highest for *Boro* rice. The factors identified in the stochastic production frontiers which are responsible for the increase of *Aus* rice production are irrigation cost, land under production, experience and education. For *Aman* rice, fertiliser, manure, land under production and education were important variables for the increase in production. For increasing the production of *Boro* rice, fertiliser, manure, ploughing cost, irrigation

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cost, insecticide cost and land under production were found to be important variables. Cobb-Douglas stochastic production frontiers included the farm-specific factors such as age, education, experience, family size and land under house. Experienced farmers tend to have smaller inefficiencies than younger and less experienced farmers. There were significant technical inefficiency effects in the production of *Boro* rice. As a policy, *Aus* and *Aman* rice crops production cannot be increased by increasing efficiency with existing technology. In this case a new advanced technology is needed to increase production. But for *Boro* rice, about 14% of production can be increased by increasing the technical efficiency only.

I. INTRODUCTION

Decisions about development strategies in agriculture are in part guided by farm level performances. These farm level performances can be attained in two ways such as to maximise output with the given set of inputs under existing production technology or to minimise production cost to produce a prescribed level of output. The former concept is known as technical efficiency. Technical efficiency is used as a measure of a firm's ability to produce maximum output from a given set of inputs under certain production technology. It is a relative concept insofar as the performance of each production unit is usually compared to a standard. This standard may be used on farm-specific estimates of best practice techniques (Herdt and Mandac 1981) but more commonly by relating farm output to population parameters based on production function analysis (Timmer 1971). A technically efficient firm will operate on its frontier production function. Given the relationship of inputs in a particular production function, the firm is technically efficient if it produces on its outer-bound production function to obtain the maximum possible output, which is feasible under the current technology. Putting it differently, a firm is considered to be technically efficient if it operates at a point on an isoquant rather than interior to the isoquant.

The measurements of crop-specific technical efficiency get momentum with increasing demands for rice in three different seasons in Bangladesh. Crop-specific efficiency measurements are particularly important for developing countries like Bangladesh where fluctuation of resources of farm households occur in different seasons. The financial stresses of farm households require judicious use of scarce resources among crops.

The measurement of the productive efficiency of a farm relative to other farms or to the "best practice" in an industry has long been of interest to agricultural economists. Efficiency measurement has received considerable attention from both theoretical and applied economists. From a theoretical point of view, there has been a spirited exchange about the relative importance of various components of firm efficiency (Leibenstein 1966; 1977; Comanor and Leibenstein 1969; Stigler 1976). From an applied perspective, measuring efficiency is important because this is the first step in a process that might lead to substantial resource savings. These resource savings have important implications for both policy formulation and firm management (Bravo-Ureta and Rieger 1991).

In the policy arena, there is a continuing controversy regarding the connection between farm size, efficiency and the structure of agricultural production. For individual farms, gains in efficiency are particularly important in periods of financial stress. Efficient farms are more likely to generate higher incomes and thus stand a better chance of surviving and prospering.

The objectives of this paper, therefore, are: (i) to develop a specification and estimation for a stochastic frontier model to estimate crop-specific technical efficiency; (ii) to estimate farm-specific technical efficiencies for different rice crops; (iii) to identify the factors causing variations in technical inefficiency effects (or technical efficiencies) among the sample farmers; (iv) to implicate certain development policies.

This paper has been organized in four sections. In section 2 data and specification of stochastic production frontier and technical inefficiency effect model are described. Section 3 contains empirical results and discussion. Some conclusions and policy implications are made in the final section.

II. DATA AND SPECIFICATION OF STOCHASTIC PRODUCTION FRONTIER AND TECHNICAL INEFFICIENCY EFFECT MODEL

Data:

This study is based on primary data which were collected from 1,360 farmers with direct interview method through pre-tested questionnaires from 14 different districts of Bangladesh. The motivation of data collection was to accomplish an FAO research project under the Programme Fund. The selection of the districts was purposive considering them as major rice growing districts and these districts contributed about 16 percent of total rice production in Bangladesh (BBS, 2008). But the selection of farmers of different categories was performed using the stratified random sampling technique. One thousand three hundred and sixty (1,360) farmers were interviewed, of which 209 farmers were *Aus* rice growers, 587 farmers were *Aman* rice growers and the other 564 farmers were *Boro* rice growers. The sampled farmers were composed of various farm categories such as marginal, small, medium and large farm households.[1] Out of the 1,360 farm households, 366 farmers were marginal, 440 farmers were small, 416 farmers were medium and the other 138 farmers were large farmers. The data were collected with the help of trained field enumerators and the data collection took place during the crop year 2008 to 2009.

Model Specification

In order to estimate the level of technical efficiency in a way consistent with the theory of production function, we have specified a Cobb-Douglas type stochastic frontier production function. The Cobb-Douglas form of production function has some well-known properties that justify its wide application in economic literature (Henderson and Quandt 1971). It is a homogeneous function that provides a scale factor, enabling one to measure the returns to scale and to interpret the elasticity coefficients with relative ease. It is also easy to estimate and manipulate mathematically. But at the same time, the Cobb-Douglas production function makes several restrictive assumptions. It is assumed that the elasticity coefficients are constant, implying constant shares for the inputs. The elasticity of substitution among factors is unity in the Cobb-Douglas form. Moreover, this being linear in logarithm, output is zero if any of the inputs is

[1] According to Bangladesh Bureau of Statistics (BBS), the categories of farm households are given below: A farmer possessing cultivable land below 50 decimal is considered to be a marginal farm, a farmer with between 51 decimal to 247 decimal is a small one, a farmer with between 248 to 750 is a medium one, and a farmer with above 750 decimal is a large one.

zero, and the output expansion path is assumed to pass through the origin. However, it is also argued that if interest rests on efficiency measurements and not on an analysis of the general structure of the underlying production technology, the Cobb-Douglas specification provides an adequate representation of the production technology. In addition, its simplicity and widespread use in agricultural economics outweigh its drawbacks. The Cobb-Douglas stochastic frontier production function is explicitly given below:

$$\ln Y_i = \ln\beta_0 + \sum_{i=1}^{10} \beta_i \ln X_i + \beta_{11} EDU + V_i - U_i \qquad (1)$$

where Y = Output (kg)

X_1 = Area under rice crops (decimal)

X_2 = Human labour (man-days)

X_3 = Seed (kg)

X_4 = Fertiliser (kg)

X_5 = Manure (kg)

X_6 = Ploughing cost (Tk.)

X_7 = Irrigation cost (real value, Tk.)

X_8 = Insecticide cost (Tk.)

X_9 = Age of farm operator

X_{10} = Experience of farm operator

EDU = Education of farm operator (year of schooling)

V_i are assumed to be independently and identically distributed random errors, having N $(0, \sigma_v^2)$-distribution; and the Ui are non-negative one-sided random variables, called technical inefficiency effects, associated with the technical inefficiency of production of the farmers involved. It is assumed that the inefficiency effects are independently distributed with a half normal distribution $(U \sim |N(0, \sigma_u^2)|)$.

The model for the technical inefficiency effects in the stochastic frontier of equation (1) is defined by

$$U_i = \delta_0 + \delta_1 AGE_i + \delta_2 EDU_i + \delta_3 EXPERIENCE_i + \delta_4 Familysize + \delta_5 FARMSZ_i + W_i \qquad (2)$$

Where AGE represents age of farm operator;
EDU is defined as earlier education;
EXPERIENCE is the experience of the farm operator;
Familysize means family size;
FARMSZ represents farm size; and
the W_i are unobservable random variables, which are assumed to be independently distributed with a positive half normal distribution.
The β- and δ- coefficients are unknown parameters to be estimated, together with the variance parameters which are expressed in terms of

$$\sigma^2 = \sigma_u^2 + \sigma_v^2 \tag{3}$$

and

$$\gamma = \sigma_u^2 / \sigma^2 \tag{4}$$

where the γ-parameter has a value between zero and one. The parameters of the stochastic frontier production function model are estimated by the method of maximum likelihood, using the computer program FRONTIER Version 4.1. It is important to note that the above model for the inefficiency effects (2) can only be estimated if the inefficiency effects are stochastic and have a particular distributional specification. Hence there is interest to test the null hypotheses that the inefficiency effects are not present, H_0: $\gamma = \delta_0 = \delta_1 = \delta_2 = \delta_3 = \delta_4 = \delta_5 = 0$. This null hypothesis of interest is tested using the generalised likelihood-ratio test and t-test. The generalised likelihood-ratio test is a one-sided test since γ can not take negative values. The generalised likelihood-ratio test requires the estimation of the model under both the null and alternative hypotheses. The test statistic is calculated as

$$LR = -2\{\ln[L(H_0)/L(H_1)]\} = -2\{\ln[L(H_0)] - \ln[L(H_1)]\} \tag{5}$$

where $L(H_0)$ and $L(H_1)$ are the values of the likelihood function under the null and alternative hypotheses, H_0 and H_1, respectively.
The technical efficiency of a farmer at a given period of time is defined as the ratio of the observed output to the frontier output which could be produced by a fully-efficient farm, in which the inefficiency effect is zero. Given the specifi-

cations of the stochastic frontier model (1) - (2), the technical efficiency of the i-th farmer can be shown to be equal to

$$\begin{aligned} TE_i &= \exp(-U_i) \\ &= \exp\{-E(U_i/\varepsilon_i)\} \\ &= 1 - E(U_i/\varepsilon_i)\} \end{aligned} \tag{6}$$

Thus the technical efficiency of a farmer is between zero and one and is inversely related to the inefficiency effect. The farm-specific efficiencies are predicted using the predictor that is based on the conditional expectation of U_i given composed error $\varepsilon_i = (V_i-U_i)$. Farm-specific or observation-specific estimates of technical inefficiency, U (subscripts can safely be omitted here), can be obtained by using the expectation of the inefficiency term conditional on the estimate of the entire composed error term, as suggested by Jondrow *et al*. (1982) and Kalirajan and Flinn (1983).

$$E(U/\varepsilon) = \sigma_* [\frac{f\left(\varepsilon\lambda/\sigma\right)}{1-F\left(\varepsilon\lambda/\sigma\right)} - \left(\frac{\varepsilon\lambda}{\sigma}\right)] \tag{7}$$

where f and F are, respectively, the standard normal density and distribution functions, evaluated at $\varepsilon\lambda/\sigma$, $\sigma_*^2 = \sigma_u^2\,\sigma_v^2/\sigma^2$, $\lambda = \sigma_u/\sigma_v$ and $\sigma^2 = \sigma_u^2 + \sigma_v^2$.

The mean technical efficiency or the mathematical expectation of the farm-specific technical efficiencies can be calculated for given distributional assumptions for the technical inefficiency effects. The mean technical efficiency can be defined by

$$\text{Mean T.E.} = E[\exp\{-E(U_i/\varepsilon_i)\}] = E[1 - E(U_i/\varepsilon_i)\} \tag{8}$$

Because the individual technical efficiencies of sample farms can be predicted, an alternative estimator for the mean technical efficiency is the arithmetic average of the predictors for the individual technical efficiencies of the sample farms. This is what is calculated by the FRONTIER (Version 4.1c) Package. With the help of FRONTIER (Version 4.1c) the parameters of the stochastic frontier production function (1) are estimated, together with farm-specific technical efficiencies and mean technical efficiency for the farms involved.

The above model has been estimated for three different rice crops, *Boro*, *Aus* and *Aman*. *Aus* is a short-duration crop which is directly seeded in March-April and harvested in July-August, utilising the pre-monsoon rainwater. *Aman*, from June-August to November-December, is the monsoon crop. It grows with the floodwaters and is harvested after the floods recede. *Boro*, from November-January to April-June, is the dry season rice crop. With the development of groundwater irrigation, *Boro* modern varieties of rice have expanded rapidly at the expense of *Aus* rice. Further, because of overlapping production cycles, area under the more profitable *Boro* has also expanded at the expense of broadcast *Aman* rice (Baffes and Gautam 2001).

III. RESULTS AND DISCUSSION

A summary of statistics on some farm-specific or socioeconomic variables used in stochastic frontier and inefficiency effect model, defined by equations (1) and (2), is presented in Table 1. All variables are expressed as per farm basis. Table 1 reveals that medium aged farmers are engaged in farming practices and the average age of farmers is 46.45 years with significant variations among crops (F = 5.51**). More aged (47.26 years) farmers were found to be working on agricultural farming in *Boro* season. Education levels of farm operators were insignificantly (F = 1.03) varied among crops and the highest education level of farmer (7.22 years) was observed in *Boro* season whereas the average education level was 7.01 years at the aggregate level. The highest experience of farmers was observed to be at 25.76 years in *Boro* season with an average experience at 25.24 years at the aggregate level and there were no significant variations of experiences of farmers among the crops (F = 1.85). The distribution of cultivable land under rice production was quite dissimilar among crops (F = 21.50**) and farmers of *Boro* crop owned the largest area under rice cultivation (239.34 decimals) with an average rice area at 220.74 decimals for all crops. Similarly, total land under households was also the highest (327.13 decimals) for the farmers in *Boro* crop and total land per household varied significantly (F = 5.22**) among crops.

TABLE 1. Crop-wise distribution of different socio-economic variables

Crop	Sample Size	Age	Education	Experience	Area Under Prod.	T. L. Under HH
		Mean (Std. deviation)	Mean (Std. deviation)	Mean (Std. deviation)	Mean (Std. deviation)	Mean (Std. deviation)
Aus	209	44.02 (12.84)	6.87 (4.12)	23.80 (11.95)	122.14 (106.78)	259.73 (180.67)
Aman	587	46.55 (12.09)	6.86 (3.99)	25.25 (12.43)	237.98 (247.50)	325.88 (290.63)
Boro	564	47.26 (11.72)	7.22 (5.26)	25.76 (12.81)	239.34 (258.19)	327.13 (286.77)
Total	1360	46.45 (12.10)	7.01 (4.58)	25.24 (12.52)	220.74 (239.88)	316.24 (275.80)
F-value		5.51**	1.03	1.85	21.50**	5.22**

Figures in the parentheses indicate standard deviations. **indicates significance at 0.01 probability level.

Table 2 summarises the farm inputs used for the production of rice crops per hectare basis among different crops. For convenience of the analysis, some of the inputs are expressed in money values. The results showed that farmers of *Boro* crop used a relatively higher amount of labour (164.27 man-days) per hectare followed by farmers of crop *Aman* and *Aus*, respectively (F = 0.293). On the other hand, farmers of *Aman* crop used a relatively higher amount of seed (48.87 kg) followed by farmers of *Boro* and farmers of *Aus* crop, respectively. Farmers of different crops used different amounts of fertiliser with significant variations (F = 120.75**) and farmers of *Boro* crop used the highest amount of fertiliser (414.53 kg), whereas farmers at the aggregate level used 350.18 kg of fertiliser. Manure use was also found to be significantly different for different crops (F = 6.83**) and the highest amount of manure was used for *Aus* crop (3732.58 kg) followed by *Boro* (3414.64 kg) and *Aman* (3014.52 kg), respectively, whereas the overall manure use was 3290.80 kg. There was no significant difference in ploughing cost among different crops (F = 0.475) and *Aman* crop exhibited the highest ploughing cost (4248.80 Tk.) per hectare followed by *Aus* and *Boro* respectively. There were significant differences (F = 561.82**) in irrigation cost among the crops, with the highest cost (Tk.4440.34) for *Boro* crop followed by *Aus* (Tk 1668.43) and *Aman* (Tk

1115.37) respectively. Insecticide cost also shows significant differences (F = 94.77**) with the highest cost for *Boro* crop (Tk.1140.67) followed by *Aus* (Tk .924.54) and *Aman* (Tk.910.87), respectively with the aggregate cost of Tk.1008.27.

TABLE 2. Crop-wise per hectare uses of different farm inputs

Crop	Sample Size	Labour (Man-Days)	Seed (kg)	Fertilizer (Kg)	Manure (Kg)	Ploughing cost (Tk.)	Irrigation cost (Tk.)	Insecticide cost (Tk.)
Aus	209	160.65 (58.86)	47.89 (15.34)	311.02 (124.15)	3732.58 (2808.25)	4155.62 (1957.76)	1668.43 (2161.08)	924.54 (307.57)
Aman	587	163.12 (59.33)	48.87 (16.32)	302.29 (136.44)	3014.52 (2560.68)	4248.80 (1876.55)	1115.37 (1765.14)	910.87 (288.08)
Boro	564	164.27 (57.43)	48.16 (19.16)	414.53 (121.95)	3414.64 (2626.03)	4141.47 (2015.89)	4440.34 (1514.03)	1140.67 (306.32)
Total	1360	163.22 (58.45)	48.43 (17.41)	350.18 (139.61)	3290.80 (2638.30)	4189.97 (1947.12)	2579.25 (2344.91)	1008.27 (318.73)
F-value		0.293	0.359	120.75**	6.83**	0.475	561.82**	94.77**

Figures in the parentheses indicate standard deviations. ** indicates significance at 0.01 probability level.

Table 3 summarises per hectare basis labour and rice production costs, gross return, net return and benefit cost ratio (BCR) among different crops. The table shows that farmers of *Boro* crop paid a significantly higher amount of labour cost (Tk.26404.33) per hectare followed by farmers of crop *Aman* and *Aus*, respectively (F = 3.03*). Similarly, farmers of *Boro* crop incurred the highest amount of production cost (Tk.64836.39) followed by farmers of *Aman* and *Aus* crop, respectively (F=39.25**). *Boro* crops exhibited the highest production per hectare (5928.09 kg) followed by *Aman* (3886.41 kg) and *Aus* crop (3291.36 kg), respectively. These yield rates were significantly different (F=662.17**) for different rice crops. There is highly significant variation among crops in terms of per hectare gross return (F = 249.38**) with the highest return for *Boro* crop (Tk.88477.77). Net returns were also found to be significantly different in different crops (F = 70.67**) and the highest amount of net return was found for *Boro* crop (23641.38 Tk.) followed by *Aman* (7786.04 Tk.) and *Aus* (1082.44 Tk.), respectively, whereas the overall net return was

Tk.13331.16. Consequently, the benefit cost ratio is highest for *Boro* crop (1.47) and has significant differences among the crops (F = 39.83**).

TABLE 3. Crop-wise per hectare cost, return and benefit cost ratio (BCR)

Crop	Per hectare Labour Cost	Per hectare Production	Per hectare gross return	Per hectare Cost	Per hectare Net Return	BCR
Aus	23993.24 (11842.50)	3291.36 (847.91)	57917.81 (16816.99)	56835.37 (16408.04)	1082.44 (24868.82)	1.11 (0.48)
Aman	25384.48 (12540.98)	3886.41 (841.38)	64788.16 (15779.87)	57002.13 (16516.63)	7786.04 (21275.57)	1.24 (0.53)
Boro	26404.33 (12471.01)	5928.09 (1413.93)	88477.77 (26613.87)	64836.39 (15677.75)	23641.38 (34136.43)	1.47 (0.64)
All	25593.62 (12425.72)	4641.66 (1567.51)	73556.57 (24643.60)	60225.42 (16605.44)	13331.16 (29207.25)	1.32 (0.58)
F-value	3.03*	662.17**	249.38**	39.25**	70.67**	39.83**

Note: Figures in the parentheses indicate standard deviation. ** and * indicate significant at 0.01 and 0.05 probability level, respectively.

Table 4 shows the simultaneous estimation of the maximum likelihood estimates for parameters of the Cobb-Douglas stochastic production frontiers and technical inefficiency effect model for *Boro*, *Aus* and *Aman* rice. If we estimate the technical efficiency effects frontier by the FRONTIER 4.1 package, we can simultaneously estimate the stochastic frontier and technical inefficiency effect model. Kumbhakar, Ghosh and McGuckin (1991), Reifschneider and Stevension (1991), Huang and Lui (1994), and Battese and Coelli (1995) specify stochastic frontiers and models for the technical inefficiency effects and simultaneously estimate all the parameters involved. This one-stage approach is less objectionable from a statistical point of view and is expected to lead to more efficient inference with respect to the parameters involved. For *Aus* rice, irrigation cost and land under production, experience, and education variables have positive and significant coefficients and the coefficient of human labour is also significant but it is negative. The negative coefficient of human labour is unusual but not surprising. It might happen due to the over-utilisation of labour in the production process as we used total human labour in the stochastic production frontier. Kalirajan and Flinn (1983) used number of pre-harvest days of labour in the stochastic production frontier and argued that labour use in harvest and onward processing activities did not influence the total volume of output. But in this study we have used total labour from land preparation to harvest and post-harvest operations and most of the economists used total labour instead of pre-harvest labour only in the production function. For *Aman* rice, fertiliser, manure, land under production and education have positive and significant coefficients. For *Boro* rice, fertiliser, manure, ploughing cost, insecticide cost, and experience variables have positive and significant coefficients, but the coefficient of human labour is negative and significant. Rahman et al. (1999) found similar results while studying technical efficiency of rice farmers in Bangladesh except positive impact of human labour on the production of *Boro* rice. Deb and Hossain (1995) found similar impacts of explanatory factors on production.

The estimated δ coefficients in Table 4 associated with the explanatory variables in the model for the inefficiency effects are worthy of deeper discussion. We observed that age and experience of farmers have negative effect upon the inefficiency effects for *Aus* rice. That is, the older more experienced farmers tend to have less inefficiency than younger and less experienced farmers. In other words, we can also say that the older and more experienced farmers are technically more efficient than the younger and less experienced farmers of *Aus* crop. Coelli and Battese (1996) found the same finding while studying technical efficiency of Indian farmers.

TABLE 4. Maximum likelihood (ML) estimates for parameters of Cobb-Douglas stochastic frontier production functions and technical inefficiency effect model for *Aus*, *Aman* and *Boro* Rice

Variables	Parameters	Rice Crops		
		Aus	*Aman*	*Boro*
Intercept:	β_0	2.2679 ** (0.2760)	2.5894 ** (0.3408)	2.8157** (0.249)
Human Labour	β_1	-0.00247 ** (0.0428)	-0.0519 (0.0215)	-0.1589** (0.0257)
Seed	β_2	-0.03204 (0.0518)	-0.0074 (0.0253)	0.0330 (0.0207)
Fertilizer	β_3	0.03466 (0.0382)	0.10611 ** (0.0135)	0.0683** (0.0187)
Manure	β_4	-0.00049 (0.0058)	0.01609 ** (0.0024)	0.0067* (0.0033)

Variables	Parameters	Rice Crops		
		Aus	*Aman*	*Boro*
Ploughing Cost	β_5	-0.0227 (0.0135)	-0.0077 (0.0106)	0.0239** (0.0087)
Irrigation Cost	β_6	0.0249** (0.0053)	0.00360 (0.0025)	-0.0018 (0.0068)
Insecticide Cost	β_7	-0.0292 (0.0499)	-0.0169 (0.0264)	0.1565** (0.0316)
Land Under Prod.	β_8	1.0338** (0.0873)	0.91907 ** (0.0389)	0.9171** (0.0478)
Age	β_9	-0.03421 (0.0883)	0.05619 (0.1096)	-0.0305 (0.0662)
Experience	β_{10}	0.0999* (0.0448)	0.03997 (0.0319)	0.0685** (0.0267)
Education	β_{11}	0.00913** (0.0039)	0.01427* (0.0074)	0.0003 (0.0022)
Inefficiency Model:				
Intercept	δ_0	-0.0066 (0.016)	-0.2634 (0.1838)	-0.6348 (1.1310)
Age	δ_1	-0.0057** (0.0021)	0.00395 (0.0027)	-0.0072 (0.0094)
Education	δ_2	0.0095 (0.126)	0.01554 (0.01006)	0.0021 (0.0087)
Experience	δ_3	-0.0078** (0.16)	-0.00533** (0.0029)	-0.0275* (0.0131)
Family Size	δ_4	-0.0031 (0.026)	0.00651 (0.0065)	0.0398 (0.0444)
Land Under HH	δ_5	-0.0032 (0.015)	-0.000081 (0.00006)	-0.00006 (0.00025)
Variance Parameters:	σ^2	0.0467 (0.17)	0.035** (0.003)	0.141 (0.123)
	γ	0.051 (0.09)	0.099 (0.124)	0.786** (0.177)
Log-likelihood Function		26.98	161.23	56.81

Note: ** and * indicate significance at 0.01 and 0.05 probability level, respectively.

Table 5 shows frequency distribution of farm-specific technical efficiency estimates for *Aus*, *Aman* and *Boro* rice from Cobb-Douglas stochastic frontiers. A careful examination of the results reveals that about 100% of sample farmers of *Aus* rice were obtaining outputs which were very close to the maximum output estimated through frontier (efficiency is 95% to 100%) and there were about 24% of sample farmers of *Aman* rice whose technical efficiency levels range from 95% to 100%, whereas 35% produced *Boro* output at 90-95% efficiency level. For *Aus* rice, technical efficiency varied from 95% to 100%, and for *Aman* rice technical efficiency varied from 70% to 100% whereas for *Boro* rice technical efficiency varied from 50% to 100%.

TABLE 5. Frequency distribution of crop specific technical efficiency estimates from Cobb-Douglas stochastic frontiers

Efficiency level	*Aus*	*Aman*	*Boro*
50-55	-	-	1 (0.2)
55-60	-	-	5 (0.9)
60-65	-	-	5 (0.9)
65-70	-	-	18 (3.2)
70-75	-	2 (0.3)	16 (2.8)
75-80	-	18 (3.1)	42 (7.4)
80-85	-	63 (10.7)	87 (15.4)
85-90	-	131 (22.3)	186 (33)
90-95	-	232 (39.5)	199 (35.3)
95-100	209 (100)	141 (24)	5 (0.9)
Total No. of farms	209 (100)	587 (100)	564 (100)

Figures in the parentheses indicate percentage.
Source: Own estimation

The average technical efficiency scores for *Aus*, *Aman*, *Boro* and all rice were respectively 0.96, 0.89, 0.86 and 0.88. The maximum efficiency scores attained for *Aus*, *Aman*, *Boro* and all rice crops were respectively 0.97, 0.98, 0.96 and 0.97, whereas the minimum efficiency scores for the above crops were respectively 0.96, 0.73, 0.53 and 0.52 (Table 6).

TABLE 6. Crop-wise technical efficiency coefficients

Efficiency Parameter	Rice Category			
	Aus	*Aman*	*Boro*	All
Maximum	0.97	0.98	0.96	0.98
Minimum	0.96	0.73	0.53	0.53
Mean	0.96	0.89	0.86	0.88

Hypothesis

We have already tested different coefficients on the Cobb-Douglas stochastic production frontiers and technical inefficiency models with the help of t-test. Here we are going to test the coefficients of farm-specific variables on the technical inefficiency effect models using generalised likelihood-ratio statistic LR. Coelli (1995) suggested that one-sided generalised likelihood-ratio test should be performed when ML estimation is involved because this test has the correct size (i.e., probability of Type I error). We have an interest in testing the null hypothesis that the inefficiency effects are not present. In other words, the null hypothesis is that there are no technical inefficiency effects in the model. That is, H_0: $\gamma = \delta_0 = \delta_1 = ... \delta_5 = 0$.

Table 7 reveals that there are significant technical inefficiency effects in the production for *Boro* rice only, since null hypothesis is rejected. For *Aus* and *Aman* crop null hypothesis is accepted.

TABLE 7. Test of hypothesis for coefficients of the explanatory variables for the technical inefficiency effects in crop specific Cobb-Douglas stochastic frontier production functions.

Null Hypothesis	Log-likelihood value	Test Statistics LR	Critical Value	Decision
H_0: $\gamma=\delta_0=\delta_1=......\delta_5=0$				
Crops:				
Aus rice	26.98	1.84	12.02	Accepted
Aman rice	161.23	10.71	12.02	Accepted
Boro rice	56.81	14.94	12.02	Rejected

Source: Own estimation

IV. CONCLUSIONS AND POLICY IMPLICATIONS

Cobb-Douglas stochastic production frontiers were estimated for *Aus, Aman* and *Boro* rice crops for this study to estimate technical efficiencies for rice crops of Bangladesh. To identify factors responsible for inefficiency effects in production, simultaneous estimation of Cobb-Douglas stochastic production frontiers and technical inefficiency effect models were performed.

The stochastic production frontiers involved land, human labour, seed, and fertiliser, manure, ploughing cost, irrigation cost, insecticide cost, age, experience, education level and family members of farm operators. Some of the parameters in the crop-specific Cobb-Douglas stochastic production frontiers were found to be significant. The identified vital factors which are responsible for the increase of production are fertiliser, manure, ploughing cost, insecticide cost and land under production. Irrigation cost, land under production, experience and education were found to have a positive and significant impact on *Aus* rice production. For *Aman* rice production, fertiliser, manure, land under production and educations were found to have a positive and significant impact on production. But for *Boro* rice fertiliser, manure, ploughing cost, insecticide cost, land under production and experiences have positive and significant impacts on production.

The models for the technical inefficiency effects in the Cobb-Douglas stochastic production frontiers included age, education, experience, family size and land under household. Older and more experienced farmers tend to have smaller inefficiencies than younger and less experienced farmers. That is, technical efficiency increased with the increase in age and experience of the farmer.

The variance ratio parameter σ^2 associated with the variances in the simultaneous estimation of Cobb-Douglas stochastic frontiers and technical inefficiency effect models is smaller for *Aus* and *Aman* crops but larger and significant for *Boro* rice. It indicates that there are inefficiency effects in the production of *Boro* crop only and the inefficiency effects are stochastic. The random component of the inefficiency effects explains that a significant portion of the difference between the observed output and the maximum production frontier output is caused by differences in farmer's levels of technical efficiency for *Boro* rice.

As a policy, for *Aus* and *Aman* rice crops production cannot be increased by increasing efficiency with existing technology. In this case new advanced technology is needed to increase production. But for *Boro* rice, production can be increased by increasing the technical efficiency only.

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