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IMPACT OF FARM-SPECIFIC FACTORS ON THE TECHNICAL INEFFICIENCY OF PRODUCING RICE IN BANGALDESH

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ABSTRACT

The rice production of Bangladesh has been investigated using a Cobb-Douglas stochastic production function which incorporates a model for the technical inefficiency effects. Farm level primary data collected by stratified random sampling technique are used for this study. The factors identified in the stochastic production frontiers which are responsible for the increase of production are extension service, farm size, bullock power, age and experience. Seed, fertilizer, human labour and irrigation cost were identified as important factors for the increase of production for only *Boro* rice and were not important factors for Aus and *Aman* rice crops. The models for the technical inefficiency effects in the Cobb-Douglas stochastic production frontiers include the farm-specific factors age, education, experience, extension contact and farm size. The factors which influence the technical inefficiency effects are identified by simultaneous estimations of stochastic production frontiers and technical inefficiency effect models for different rice crops. The study reveals that the impacts of age,, experience, extension contact and farm size on the technical inefficiency effects are significantly negative which means that technical inefficiency effects decrease significantly with the increase in the magnitudes of these factors. The study also indicates that there are significant technical inefficiency effects in the production of all rice crops and 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 farmers' levels of technical efficiency.

I. INTRODUCTION

Scarcity of resources has led production economists to think about the reallocation of existing resources to have more output with minimum input combinations or with the minimum cost without changing the production technology. Producers wish to maximize profit within the constraint of given costs or limited resources under certain production technologies whereas consumers wish to maximize their total utility or satisfaction by allocating their limited budgets (income constraint) among different types of commodity bundles. Producers have to decide

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what to produce, how much to produce, what method of production to use, where to sell and buy and when to sell and buy. All these decisions of producers are due to the fact of scarce or limited resources. In the farming sector, production theory aims at analysing how the farm operator combines various limited inputs to produce a maximum amount of output in an economically efficient manner under certain technology.

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.

Technical efficiency refers to the ability of a firm to produce maximum possible output with a minimum quantity of inputs, under a given technology. 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 homogeneity of inputs is a vital factor for achieving technically efficient output. No one would dispute that the output produced from given inputs is a genuine measure of efficiency, but there is room for doubt whether, in a particular application, the inputs of a given firm are really `the same' as those represented by the corresponding point on the efficient isoquant. But it is important to note that mere heterogeneity of factors will no matter, so long as it is spread evenly over firms. Only when there are differences between firms in the average quality (or, more strictly, in the distribution of qualities) of a factor, that a firm's technical efficiency will reflect the quality of its inputs as well as the efficiency of its management. If these differences in quality are physically measurable, it may be possible to reduce this effect by defining a large number of relatively homogeneous factors of production, but in practice it will never be likely to eliminate it completely (Farrell 1957).

Economic development in Bangladesh mainly depends on the progresses to be made in the agricultural sector, but agricultural development is dependent on appropriate policies relating to augmenting productivity and efficiency of agricultural crops. Increase of productivity and efficiency are based on some socio-economic and demographic variables. Proper policies can be formulated only after the empirical measurement of the core variables. The accuracy of the identification of the impact of different variables depends on the functional form of the production technology (whether Cobb-Douglas or Translog or CES), the nature of the random error component (whether stochastic or deterministic), the distribution of the inefficiency component (whether it is half normal or truncated normal or gamma or beta), the nature of the production function (whether primal or dual) etc.

Economic relationships based on optimization behaviour define efficient frontiers of minimum (e.g. cost) or maximum (e.g. production) attainment. Traditional econometric methods for estimating stochastic economic relationships have implicitly assumed that all economic agents are successful in reaching the efficient frontier. If, however, the economic agents are not equally efficient, then the average relationships estimated by ordinary least squares methods might not reflect the frontier relationships (STEVENSON, 1980). Our purpose here is to develop a specification and estimation for a stochastic frontier model.

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 discussions. Some conclusions are made in the final section

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

Data:

The three regions, that is, Brahmanbaria, Mymensingh and Dinajpur were selected purposively considering the relative importance of these regions in producing rice. These three great regions (old district) produce about 16 percent of total rice in Bangladesh (BBS 1998). Considering their contribution to the total output, the selection of these regions was appropriate for a study on the efficiency of rice production. Moreover, soil texture of these regions represents the soil texture of the country. Farmers of these regions are familiar with new inputs of production such as HYV* seeds, artificial irrigation, chemical fertilizer etc. for several years and in these regions there are the requisite number of households with different farm sizes. The regions are also relatively easily accessible and well communicated. Since Dinajpur is the north-west district of the country, Mymensingh is the middle district and Brahmanbaria is the south-east district, the selection of these areas was uniform on the spatial context.

To collect the primary data from the farmers of Bangladesh probability sampling technique was adopted. At first a sampling frame of farmers was constructed with the help of village leaders and some other relevant persons. The villages were selected with simple random sampling technique but the farmers were selected with stratified random sampling with arbitrary allocation. The data were collected for the crop year July 1998 to June 1999. The sample composed of small (below 1.00 hectare), medium (1.00-3.00 hectare) and large (above 3.00 hectares) farms. Within sample, 50 percent are small, 30 percent are medium and 20 percent are large farmers. Five hundred farmers in total were interviewed in this study. Of the five hundred samples, 300 farmers had direct contact with extension workers and were selected 100 from each region to have an idea on importance of extension service in Bangladesh. Another 200 farmers, those who had no relation with the extension workers were selected 100 from each region except Mymensingh region. For the region **Mymensingh** only a sample of 100 farmers with extension service was collected but no sample of non-extension farmers was collected because there is one agricultural university known as **Bangladesh Agricultural University** and from this university every year several extension programmes are carried out in this region side by side government extension programmes. Thus farmers of this region are more or less related with extension programmes. To have a comparison of the productivities between farmers with extension services and farmers without extension services, these two types of data are very much useful.

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 mathematically manipulate. On the other hand, 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 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 explicit Cobb-Douglas stochastic frontier production function is given below:

$$\ln Y_i = \ln \beta_0 + \sum_{i=1}^{9} \beta_i \ln X_i + \beta_{10}\,EDU + \beta_{11}\,EXT + V_i - U_i \qquad (1)$$

where Y = Output (kg)

X_1= Area under rice crops (hectare)

X_2= Human labour (man-days)

X_3= Seed (kg)

X_4= Fertilizer (kg)

X_5= Manure (kg)

X_6= Bullock power (pair-days)

X_7= Irrigation cost (real value, Taka)

X_8= Age of farm operator

X_9= Experience of farm operator

EDU = Education of farm operator (year of schooling)

EXT = Extension service (Dummy variable which receives 1 if the farm had contact with extension agents and receives 0 if it did not have any contact with extension agents)

Vi are assumed to be independently and identically distributed random errors, having N $(0,\sigma_v^2)$-distribution; and the U_i 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

$$U_i = \delta_0 + \delta_1 \text{ AGE}_i + \delta_2 \text{ EDU}_i + \delta_3 \text{ EXPERIENCE}_i + \delta_4 \text{ CONTACT}_i + \delta_5 \text{ FARMSZ}_i + W_i \quad (2)$$

Where AGE represents age of farm operator;

EDU is defined as earlier;

EXPERIENCE is the experience of the farm operator;

CONTACT represents extension contact by the extension agents to the farmers;

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

$$\sigma^2 = \sigma_u^2 + \sigma_v^2 \quad (3)$$

and

$$\gamma = \sigma_u^2/\sigma^2 \quad (4)$$

where the γ-parameter has a value between zero and one. The parameters of the stochastic frontier production function model are estimated by the maximum likelihood method, using the computer program, FRONTIER Version 4.1.

The expected signs on the δ-parameters in the inefficiency model, defined by equation (2), are not clear in all cases. The age of the farmers could be expected to have a positive or a negative effect upon the size of the inefficiency effects. The older farmers are likely to have had more farming experience and hence have less inefficiency. However, they are also likely to be more conservative and thus be less willing to adopt new practices, thereby perhaps having greater inefficiencies in agricultural production.

Education of farmers is expected to have a negative effect upon the inefficiency effects. That is, we expect that greater levels of formal education will be associated with smaller values for the inefficiency effects. It may also happen that if the farmers with more formal education have alternative sources of income, or if they are not attentive with farming practices and rely more on fixed labourer those who are not educated, may have positive effect upon the inefficiency effects.

Experiences of farmers are expected to have a negative impact upon the inefficiency effects and it is generally assumed that farmers with more experiences of farming practices are more efficient than farmers with less experiences.

Contact of extension agents with the farmers is expected to have a negative impact upon the inefficiency effects. That is, farmers with more contacts with the extension agents are likely to be more efficient than farmers with less extension contacts.

The sign of the coefficient of the land or farm size variable in the model for the inefficiency effects is expected to be negative. This expectation is partially based upon the likelihood that the farmers with smaller operations may have alternative income sources which are more important and hence put less effort into their farming operations compared with the larger farmers.

It is important to note that the 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: $\gamma = \delta_0 = \delta_1 = \delta_2 = \delta_3 = \delta_4 = \delta_5 = 0$; the inefficiency effects are not stochastic, $H_0 : \gamma = 0$; and the coefficients of the variables in the model for the inefficiency effects are zero, $H_0 : \delta_1 = \delta_2 = ... = \delta_5 = 0$. These and other null hypotheses of interest are tested using the generalized likelihood-ratio test and t-test. The generalized likelihood-ratio test is a one-sided test since γ can not take negative values. The generalized likelihood-ratio test requires the estimation of the model under both the null and alternative hypotheses. Under the null hypothesis, $H_0 : \gamma = 0$, the model is equivalent to the traditional average response function, without the technical inefficiency effect, U_i. 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.

If H_0 is true, this test statistic is usually assumed to be asymptotically distributed as a chi-square random variable with degrees of freedom equal to the number of restrictions involved. However, difficulties arise in testing H_0: $\gamma = 0$ because $\gamma = 0$ lies on the boundary of the parameter space for γ. In this case, if H_0: $\gamma = 0$ is true, the generalized likelihood-ratio statistic LR, has asymptotic distribution which is a mixture of chi-square distributions, namely $\frac{1}{2}\chi_0^2 + \frac{1}{2}\chi_1^2$, (COELLI 1995a).

The calculation of the critical value for this one-sided generalized likelihood-ratio test of H_0: $\gamma = 0$ versus H_1: $\gamma > 0$ is quite simple. The critical value for a test of size α is equal to the value, χ_1^2 (2α), where this is the value which is exceeded by the χ_1^2 random variable with probability equal to 2α. Thus the one-sided generalized likelihood-ratio test of size α is: "Reject H_0: $\gamma = 0$ in favour of H_1: $\gamma > 0$ if LR exceeds χ_1^2 (2α)". Thus the critical value for a test of size, $\alpha = 0.05$, is 2.71 rather than 3.84 for degree of freedom one.

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 firm, in which the inefficiency effect is zero. Given the specifications of the stochastic frontier model (1) – (2), the technical efficiency of the i-th farmer can be shown to be equal to

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

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 $\varepsilon_i = (V_i - U_i)$.

Firm-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, LOVELL, MATEROV, and SCHMIDT (1982) and KALIRAJAN and FLINN (1983). One can use either the expected value or the mode of this conditional distribution as an estimate of U:

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

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 $\sigma^2 = \sigma_u^2 + \sigma_v^2$.

AIGNER, LOVELL and SCHMIDT (1977), JONDROW et al. (1982); BRAVO-URETA and RIEGER (1991) and others expressed the likelihood function in terms of the two variance parameters, $\sigma^2 = \sigma_u^2 + \sigma_v^2$ and $\lambda = \sigma_u/\sigma_v$. But they interpreted λ to be an indicator of the relative variability of the two sources of the random error that distinguish firms from one another. Here $\lambda = \sigma_u/\sigma_v$ is the ratio of the standard deviation of the non-negative error term U_i to the standard deviation of the two-sided symmetric error term V_i. If λ approaches 0 then it implies σ_v very large or σ_u is close to zero, i.e. the symmetric error dominates in the determination of ε and the density function of ε becomes the density of a $N(0,\sigma^2)$ random variable. In other words, the discrepancy between the observed and the frontier output is dominated by random factors beyond the control of the farmer. Similarly, when σ_v is close to zero (i.e. $\sigma_v \rightarrow 0$), λ becomes very large (i.e. $\lambda \rightarrow \alpha$) and the one-sided error becomes the dominant source of random variation in the model and hence the production process is characterised by technical inefficiency, where density of ε takes on the form of a negative half-normal. Some other authors (BATTESE and CORRA 1977; BATTESE and COELLI 1992; COELLI and BATTESE 1996; KALIRAJAN 1981, 1984; KALIRAJAN and FLINN 1983; KALIRAJAN and SHAND 1985) have used different parameter $\gamma = \sigma_u^2/\sigma^2$ to explain the discrepancy between the frontier output level and the actual output. Battese and Corra (1977) suggested that the parameter, $\gamma = \sigma_u^2/\sigma^2$, be used because it has a value between zero and one, whereas the λ-parameter could be any non-negative value. They also suggested that the γ-parameterisation has advantages in seeking to obtain the ML estimates because the parameter space for γ can be searched for a suitable starting value for the iterative maximization algorithm involved.

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

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

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 FRONTIER (Version 4.1c) Package. With the help of the FRONTIER programme 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. However, the arithmetic mean may not be the best estimator when the sample farms have significantly different sizes of operations or are not obtained by a simple random sampling from the population of the farms.

The above model has been estimated for three different rice crops, Boro, Aus and Aman, and for all and different regions separately. The data used in this model are cross-sectional data and sample sizes for Boro, Aus and Aman rice are 490, 82 and 460, respectively. Table 2 presents the maximum likelihood estimates of the stochastic production frontier. For comparison purposes OLS estimates are also shown.

III. RESULTS AND DISCUSSION

A summary of the sample data on the different variables in the stochastic frontier and technical inefficiency effect model, defined by equations (1) and (2), respectively , is presented in Table 1. All variables are expressed in Table 1 as per hectare or per farm basis. The sizes of land holdings are very small relative to those seen in modern western agriculture. The average farm sizes vary from 1.88 hectares in Brahmanbaria region to 2.31 hectares in Dinajpur region. The farmers of Bangladesh produce three rice crops which are *Boro*, *Aus* and *Aman* (local name) in three different seasons. Table 1 reveals that the productivities of different rice crops vary in different regions. The average yield rate of *Boro* rice is the highest in Brahmanbaria region which is 6795.12 kg/ha followed by 6481.24 kg/ha in Dinajpur region and 4808.05 kg/ha in Mymensingh region. There is significant difference of productivity of Boro rice among regions (F=4.67**). A Duncan's test suggests that there is no difference of productivity of Boro between Brahmanbaria region and Dinajpur region but their productivities are significantly higher than that of Mymensingh region. The average yield rate of *Aus* rice is 4287.01 kg/ha in Dinajpur region and 2205.52 kg/ha in Brahmanbaria region. Farmers of Dinajpur region produce significantly more (F=50.82**) Aus rice per hectare than farmers of Brahmanbaria region. But no farmer of Mymensingh region was found to produce *Aus* rice. The average yield rate of *Aman* rice is the highest in Dinajpur region which is 3631.84 kg/ha followed by 3593.56 kg/ha in Mymensingh region and 2577.04 kg/ha in Brahmanbaria region. A

Duncan's test suggests that farmers of Dinajpur and Mymensingh regions produce same level of *Aman* rice per hectare and they produce significantly more rice than farmers of Brahmanbaria region. Dinajpur region has absolute advantage of producing all rice crops. Cost of production per hectare varies significantly among

Table 1. Summary Statistics for Variables in the Stochastic Frontier Production Functions for Farmers in Three Regions of Bangladesh

	Sample Mean								
	Brahmanbaria			Dinajpur			Mymensingh		
	Boro	Aus	Aman	Boro	Aus	Aman	Boro	Aus	Aman
Crop Yield (kg./hectare)	6795.12 (7542.82)	2205.52 (809.96)	2577.04 (695.12)	6481.24 (2031.67)	4287.01 (1216.11)	3631.84 (3098.71)	4808.05 (5019.50)		3593.56 (2290.12)
Per hectare revenue (Taka)	57766.89 (64577.53)	21105.69 (8830.55)	23777.35 (7907.67)	49380.99 (16709.35)	29600.52 (7210.50)	30959.44 (25117.27)	43710.18 (39562.85)		31186.02 (17821.28)
Cost of Production (Taka/hectare)	36042.80 (8623.58)	15672.10 (6361.71)	18499.36 (7487.71)	26995.07 (11494.32)	20671.16 (11286.08)	15373.12 (10836.53)	30974.54 (9364.89)		20212.42 (12326.83)
Land (hectare/farm)	1.88 (3.13)			2.39 (2.94)			2.31 (3.91)		
Seed (kg/hectare)	51.52 (63.83)	63.77 (29.63)	65.26 (51.49)	55.30 (33.20)	99.50 (141.15)	56.06 ((28.86)	59.91 (60.51)		52.17 (46.80)
Human labour (Man-days/hectare	215.86 (60.70)	138.38 (50.82)	151.74 (57.90)	140.63 (78.56)	96.68 (26.56)	115.77 (75.77)	213.90 (94.00)		186.70 (84.53)
Bullock Power (Pair-days/hectare)	20.71 (8.82)	14.45 (9.31)	18.07 (7.97)	26.65 (12.61)	32.01 (22.65)	24.15 (19.66)	33.83 (32.95)		29.95 (31.53)
Fertilizer (kg/hectare)	458.70 (171.25)	127.14 (141.25)	59.77 (93.12)	320.17 (120.07)	383.33 (165.22)	168.58 (259.23)	430.66 (206.17)		273.26 (143.91)
Manure (kg/hectare)	1284.22 (2581.44)	2062.88 (3066.69)	1013.92 (2216.02)	5531.24 (5757.29)	4103.08 (4248.18)	3619.33 (4309.00)	3991.71 (4427.62)		931.92 (1264.76)
Irrigation cost for Boro (Taka/hectare)	4250.55 (3169.50)			5123.62 (1538.78)			5680.74 (5906.91)		
Age of farm operator (year)	50.03 (12.13)			42.87 (11.27)			47.79 (11.85)		
Experience of farm operator (year)	27.15 (13.11)			18.72 (9.76)			25.26 (12.10)		
Education of farm operator (year of schooling)	6.10 (4.09)			8.81 (3.49)			7.11 (4.16)		

Source: Field Survey 1999.

regions and among rice crops. There are no significant difference of seed/ha used by farmers among regions for *Boro* rice but for *Aus* rice farmers of Dinajpur region used significantly more seed than farmers of Brahmanbaria region. For *Aman* rice, farmers of Dinajpur and Mymensingh regions used about same level of seed but they used significantly less amount than the Brahmanbaria region. Uses of human labour, bullock power, fertilizer and manure per hectare show also significant difference among crops and also among regions. Farmers do not need to irrigate their lands to produce *Aman* and Aus rice. Average cost of irrigation for Figures in the parentheses indicate standard deviations.

Boro rice varies Taka 4250.55 in Brahmanbaria region to Taka 5680.74 in Mymensingh region. Average ages of farm operators for Brahmanbaria, Dinajpur and Mymensingh are respectively 50.03, 42.87 and 47.79 years. Since more younger farmers are engaged in farming practices in Dinajpur regions, their experiences of farming are also less than those of other regions. Education levels of farm operators also vary among regions.

The maximum likelihood estimates for parameters of the Cobb-Douglas stochastic production frontiers for *Boro, Aus* and *Aman* rice among all regions are presented in Table 2. For comparison purposes OLS estimates are also shown. For *Boro* rice most of the parameters are statistically significant and all parameters have expected signs except parameter of education (EDU) variable in both models. The sign of the parameter for the education variable is negative and significant (at the 1% level) which is unexpected but not surprising. Negatively significant parameter of education means that the rate of output decreases with the increase in education of farm operators. One of the reasons may be that most of the educated farmers were found to have alternative income sources (service, business etc.) and they are not very much attentive with the farming practices and in that case they rely mostly on the fixed labourers those who have minimum education or no education at all. Another reason to include is that most of the educated farmers are village leaders and they were found to be busy with the problems of villagers and many of them were found to be engaged in local or national politics. For that reason they have little time for their farming practices. Indeed, there have been many empirical tests of the effect of education on farm productivity. These generally have employed Cobb-Douglas production functions. LOCKHEED et al. (1980) have surveyed many of these studies. Although they conclude that the effect of education on productivity is positive, a significant number of studies (40%) found either a negative effect or no impact on

Table 2. Ordinary Least Squares (OLS) Estimates of a Cobb-Douglas (C-D) Production Function and Maximum Likelihood (ML) Estimates of a C-D Stochastic Production Frontier.

Variables	Rice crops					
	Boro		Aus		Aman	
	OLS estimates (std. error)	ML estimates (Asymptotic std. error)	OLS estimates (std. error)	ML estimates (Asymptotic std. error)	OLS.estimates (std. error)	ML estimates (Asymptotic std. error)
Intercept	3.479** (0.139)	3.636** (0.132)	3.481** (0.987)	3.553** (0.966)	4.245** (0.404)	4.539** (0.418)
Education (EDU)	-0.0000117** (0.00000051)	-0.0000117** (0.00000048)	-0.0000096** (0.0000015)	-0.0000096** (0.0000014)	-0.0000104** (0.00000075)	-0.0000104** (0.00000074)
Extension (Dummy)	0.00752* (0.00379)	0.00894** (0.00377)	0.00899 (0.0134)	0.00991 (0.0133)	0.01816** (0.00575)	0.0187** (0.00569)
Area	0.0709** (0.0204)	0.0709** (0.0201)	0.0000409** (0.0000035)	0.0000406** (0.0000034)	0.0000339** (0.0000015)	0.0000585** (0.0000015)
Human labour	0.626** (0.054)	0.626** (0.046)	0.03885 (0.135)	0.03885 (0.134)	0.07579 (0.0596)	0.06555 (0.0595)
Seed	0.00000615** (0.00000074)	0.00000681** (0.00000066)	0.00000444* (0.00000209)	0.00000545* (0.00000207)	-0.00000124 (0.000000871)	-0.00000117 (0.000000865)
Fertilizer	0.0531* (0.0261)	0.0531* (0.0252)	-	-	-	-
Manure	0.000000943 (0.00000068)	0.000000901 (0.00000067)	-	-	-	-
Bullock power	0.0687* (0.0356)	0.07701** (0.0333)	0.6147** (0.1072)	0.6772** ((0.1070)	0.7063** (0.0289)	0.7075** (0.0285)
Irrigation cost	0.00000049 (0.00000063)	0.00000048 (0.00000059)	-	-	-	-
Age	0.2096** (0.0397)	0.1912** (0.0350)	0.2307* (0.1177)	0.2407* (0.1167)	0.2097** (0.0566)	0.2633** (0.0562)
Experience	0.00000234** (0.00000071)	0.00000256** (0.00000063)	0.1901 (0.2904)	0.2103 (0.2803)	0.03712 (0.1258)	0.01285 (0.1263)
Function coefficient	1.04	1.04	1.08	1.08	1.05	1.07
F-statistic model	162.26**	-	8.33**	-	101.69**	-
Adj. R^2	0.86	-	0.77	-	0.85	-
Variance Parameters:						
σ^2	0.111	0.348** (0.0148)	0.176	0.262** (0.0315)	0.207	0.263** (0.0414)
γ	-	0.819** (0.0199)	-	0.500** (0.0719)	-	0.363* (0.1676)
Log-likelihood function	-150.05	-73.37	-40.46	-26.48	-285.52	-164.19

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

Source: Own estimation.

productivity. Slope parameters across equations are similar, which suggests that the frontier function represents a neutral upward shift of the OLS model. The function coefficient in both the frontier and the OLS model is 1.04. Coefficient of extension service is positive and significant which means that government extension service has positive impact on the increase of production. We can also say that extension farmers are more productive than non-extension farmers. Area, human labour, seed, fertilizer. bullock power, age and experience have significantly positive contribution on the increase of production since their coefficients were found to be significantly positive. The coefficients of manure and irrigation cost are positive but not significant. The coefficient of multiple determination for *Boro* rice is 0.86 which means that 86% of total production is explained or contributed by the explanatory variables used in the model. The model (OLS) is well fitted to the data since F-test used to test the goodness of fit was found to be highly significant (significant at 1% level). The farmspecific technical efficiency coefficients for *Boro* rice derived from the above stochastic frontier vary from 54% to 96% and their mean technical efficiency is 86% (Table 4). An important result is that the variance ratio parameter y is comparatively large (0.819), given the interval within which it lies and is statistically significant at the 1% level. This means that about 82 percent of the difference between the obseryed output and the maximum production frontier output is caused by differences in farmers' levels of technical efficiency as opposed to the conventional random variability.

For *Aus* and *Aman* rice, most of the farmers do not use fertilizer and manure and we have deleted these variables from the model. Since *Aus* rice is produced in the rainy season, farmers do not need to irrigate their lands and accordingly irrigation cost is excluded from the model of *Aus* rice. Farmers do not need to irrigate *Aman* land also. For *Aus an*d *Aman* rice also the frontier functions represent a neutral upward shift of the OLS models since slope parameters across equations are similar. The coefficients of education variable for *Aus* and *Aman* rice are negative and significant which means that the rate of output for these crops decreases with the increase in education of farmers. The coefficients of extension variable for *Aus* and *Aman* rice are positive but for *Aus* rice the coefficient is insignificant while it is significant for *Aman* rice. Area variable is found to have a significantly positive contribution on the increase of both *Aus* and Aman output. Human labour has positive but not significant impact on the increase of both *Aus* and *Aman* rice. The coefficient of seed is positive and significant for *Aus* rice but it is negative and insignificant for *Aman* rice. Bullock power is important factor which is found to have a significantly positive impart on both the *Aus* and *Aman* rice outputs. Age of the farmers has a positive and significant effect on both *Aus* and *Aman* rice production while the coefficient of experience is found to be positive but not significant for both these rice crops. Both the models are well fitted to the data. Adjusted R^2shows that about 77% of *Aus* rice production is explained by the explanatory variables included in the model while for *Aman* rice 85% of production is explained by the above variables. Farmspecific technical efficiencies for *Aus* and *Aman* ice vary from 92% to 95% and 39% to 93% with average technical efficiency 93% and 80%, respectively. Variance ratio parameter y is statistically significant at the 1% level for both *Aus* and *Aman* rice. This means that about 50% (for *Aus* rice) and 36% (for *Aman* rice) of the difference between the observed output and the maximum production frontier output is caused by differences in farmers' levels of technical efficiency as opposed to the conventional random variability.

Table 3 shows the simultaneous estimation of the maximum likelihood estimates for parameters of 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 FRONTIER 4.1 package, we can simultaneously estimate the stochastic frontier and technical inefficiency effect model. The stochastic frontier estimated simultaneously is a little bit different in respect of some significant coefficients from the earlier one presented in Table 2 since the earlier frontiers were estimated with a single estimation procedure. Although the second estimation procedure has simultaneous-equation bias, it is also important to identify the factors which influence the technical inefficiency of farmers. 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. But most of the researchers used two-stage approach to explain the differences in technical efficiencies of farmers. The first stage involves the estimation of a stochastic frontier production function and the prediction of farm-level technical inefficiency effects (or technical efficiencies). In the second stage, these predicted technical inefficiency effects (or technical efficiencies) are related to farmer-specific factors using Ordinary Least Squares (OLS) regression (KALIRAJAN 1981; PARIKH and SHAH 1994). This two-stage approach is more objectionable from a statistical point of view. Table 3 reveals that for *Boro* rice extension, human labour, seed,

Table 3. Maximum Likelihood (ML) Estimates for Parameters of Cobb-Douglas Stochastic Production Frontier Functions and Technical Inefficiency Effect Model for *Boro*, *Aus* and *Aman* Rice

Variables	Parameters	Rice crops		
		Boro	***Aus***	***Aman***
Stochastic Frontier:				
Intercept	β_0	3.66487** (0.13028)	5.646703** (1.23827)	5.33988** (0.36731)
Education (EDU)	β_1	-0.00001182** (0.00000052)	-0.00000995** (0.00000129)	-0.00000831** (0.00000065)
Extension (Dummy)	β_2	0.00825* (0.00383)	0.00967458 (0.0114258)	0.011887* (0.00534)
Area	β_3	-0.06293 (0.04129)	0.00000379** (0.00000123)	0.0000025* (0.0000012)
Human labour	β_4	0.68233** (0.05294)	0.007801826 (0.11337730)	-0.044411 (0.044729)
Seed	β_5	0.000006709** (0.00000075)	-0.00000265 (0.00000175)	-0.00000049 (0.00000074)
Fertilizer	β_6	0.07499* (0.03583)	-	-
Manure	β_7	0.00000107 (0.00000069)	-	-
Bullock power	β_8	0.03569 (0.03592)	0.7612193** (0.1725159)	0.64954** (0.036802)
Irrigation cost	β_9	0.000000025 (0.00000058)	-	-
Age	β_{10}	0.15364** (0.03492)	0.34402435 (0.1151759)	-0.140091** (0.051822)
Experience	β_{11}	0.000001602* (0.00000066)	-0.19449378 (0.25152956)	0.1612939 (0.100812)
Inefficiency Model:				
Intercept	δ_0	-0.000000000041 (0.000000000033)	2.003633* (0.814667)	1.59587** (0.1721)
Age	δ_1	-0.000000000031** (0.000000000011)	-0.0000091** (0.0000022)	-0.0000092** (0.0000016)
Education	δ_2	0.00000173 (0.0000012)	0.0843766 (0.1158312)	-0.05613 (0.05060)
Experience	δ_3	-0.000000000036* (0.000000000016)	-0.00000186 (0.00000194)	-0.00000215* (0.00000099)
Extension contact	δ_4	-0.0000000239** (0.0000000035)	-0.15929535* (0.07758695)	-0.25741** (0.05785)
Farm size	δ_5	-0.000000000158* (0.000000000071)	-0.00000198 (0.00000151)	0.00000029 (0.00000084)
Variance Parameters:				
	σ^2	0.134* (0.0651)	0.1017** (0.0162)	0.129** (0.0096)
	γ	0.680** (0.2159)	0.999** (0.1701)	0.787** (0.095)
Log-likelihood function		-152.34	-22.60	-164.11

** and * indicate significance at 0.01 and 0.05 probability level, respectively.
Source: Own estimation.

fertilizer, age and experience variables have positive and significant coefficients and the coefficient of education is also significant but it is negative. For *Aus* rice, area and bullock power have significant coefficients but education has significantly negative impact on production. For *Aman* rice, extension, area and bullock power are found to have positive and significant coefficients but education and age have significantly negative coefficients.

The estimated 8-coefficients in Table 3 associated with the explanatory variables in the model for the inefficiency effects are worthy of deeper discussion. We observe that age of the farmers has a significantly negative effect upon the inefficiency effects for all rice crops. That is, the older farmers tend to have smaller inefficiencies than younger farmers. In other words, we can also say that the older farmers are technically more efficient than the younger farmers. COELLI and BATTESE (1996) found the same finding while studying technical efficiency of Indian farmers.

Education is found to have no effect upon the technical inefficiency effects for all rice crops since its coefficient is insignificant for these crops. KALIRAJAN and FLINN (1983) and other researchers did not find any impact of formal education on the technical inefficiency effects.

Experience of farm operators has negative and significant effect upon the inefficiency effects for *Boro* and *Aman* rice. This means that the inefficiency effects decrease with the increase of the experiences of farm operators for *Boro* and *Aman* rice. That is, technical efficiency increases with the increase of experiences of the farmers for *Boro* and *Aman* rice. Experienced farmers can manage and allocate inputs more efficiently than less experienced farmers. For *Aus* rice, the effect of experience upon the inefficiency effect is also negative but not significant. These findings are in conformity with findings of HERDT and MANTAC (1981) and KALIRAJAN (1984). They found that technical efficiency increases with the increase in experiences of farmers.

Extension contact has significantly negative effect upon the inefficiency effects for *Boro*, *Aus* and *Aman* rice. That is, farmers with more extension contacts with the extension agents are more technically efficient than farmers with less extension contacts or with no contact at all. In other words, we can say that the technical inefficiency effect decreases with the increase in the number of extension contact of extension agents with the farmers. The same result was found by KALIRAJAN (1984), HERDT and MANTAC (1981). KALIRAJAN (1984) studied technical efficiency of rice farmers in Philippines. He found that technical efficiency increases with the increase in the number of extension contacts. He also showed that there existed a wide variation in the level of technical efficiencies among the sample farmers and an extension service had been identified as an important factor causing such variations. HERDT and MANTAC (1981) concluded in their study that the lack of effective extension service was responsible for lower output in the Philippines.

The coefficient of the farm size variable in the model for the inefficiency effect is estimated to be significantly negative for *Boro* rice. This indicates that farmers with larger farms tend to have smaller inefficiency effects than farmers with smaller operations. The same phenomenon was observed by COELLI and BATTESE (1996) while studying technical efficiency of Indian farmers. This contradicts the claim which is frequently made for developing country agriculture, that smaller farmers tend to be more efficient in production than larger farms. The coefficient of farm size for *Aus* rice is also negative in the inefficiency effect model but it is not found to be significant while the corresponding coefficient for *Aman* rice is positive and insignificant.

The γ-parameter associated with the variances in the stochastic frontier is significant for all rice crops. It indicates that there are inefficiency effects in the production of rice crops and the random component of the inefficiency effects does make a significant contribution in the analysis of agricultural production.

Table 4 shows frequency distribution of farm-specific technical efficiency estimates for *Boro, Aus* and *Aman* rice from Cobb-Douglas stochastic frontiers. A careful examination of the results reveals that only about 5% of sample farmers were obtaining outputs which were very close to the maximum output estimated through frontier (efficiency is 90% to100%) and there are about 92% of sample farmers whose technical efficiency levels range from 80% to 90% for *Boro* rice. The average technical efficiency computed for *Boro* rice is 86%.

Table 4 reveals that for *Aus* rice all of the farmers were found to produce outputs which were very close to the maximum frontier outputs (efficiency levels vary from 90%. to 100%) The average technical efficiency computed for *Aus* rice is 93%.

An examination of farm-specific technical efficiency for *Aman* rice reveals that only about 2% of sample farmers were obtaining outputs which were very close to the frontier maximum outputs (efficiency 90% or more), and the rest were far below the frontier. The average technical efficiency computed for *Aman* rice is 80%.

Table 4. Frequency Distribution of Farm-Specific Technical Estimates from Cobb-Douglas Stochastic Frontiers.

Efficiency level (%)	Boro rice	Aus rice	Aman rice
	Technical Efficiency	Technical Efficiency	Technical Efficiency
35-40	0	0	1 (0.22)
40-45	0	0	1 (0.22)
45-50	0	0	0
50-55	1 (0.20)	0	0
55-60	1 (0.20)	0	1 (0.22)
60-65	2 (0.41)	0	2 (0.44)
65-70	1 (0.20)	0	15 (3.26)
70-75	2 (0.41)	0	55 (11.96)
75-80	8 (1.64)	0	120 (26.08)
80-85	103 (21.02)	0	203 (44.13)
85-90	347 (70.82)	0	53 (11.52)
90-95	24 (4.90)	75 (91.46)	9 (1.95)
95-100	1 (0.20)	7 (8.54)	0
Total number of farms	490 (100.00)	82 (100.00)	460 (100.00)
Mean Efficiency	86	93	80
Minimum Efficiency	54	92	39
Maximum Efficiency	96	95	93

Figures in the parentheses indicate percentage.
Source: Own estimation

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 generalized likelihood-ratio statistic, LR. Coelli

(1995) suggested that one-sided generalized likelihood-ratio test should be performed when ML estimation is involved because this test has the correct size (i.e., probability of a Type I error). We have interest to test 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 5 reveals that there are significant technical inefficiency effects in the production of all rice crops in all regions since null hypothesis is rejected for all rice crops. For region-specific efficiency measures for *Boro* rice, there is no inefficiency effect in Brahmanbaria region but technical inefficiency effects are found to be significant in Dinajpur and Mymensingh regions. There are significant technical inefficiency effects in all regions in the production of *Aman* rice since null hypothesis is rejected in all regions. For *Aus* rice we could not estimate region-specific stochastic production frontier since data did not permit it.

Table 5. Test of Hypotheses for Coefficients of the Explanatory Variables for the Technical Inefficiency Effects in the Cobb-Douglas Stochastic Frontier Production Functions.

Null Hypothesis	Log-likelihood value	Test statistic LR	Critical value	Decision
$H_0{:}\gamma = \delta_0 = \delta_1 = \ldots = \delta_5 = 0$.				
All regions,				
Boro	-152.34	15.36	12.02	Rejected
Aus	-22.60	35.72	12.02	Rejected
Aman	-164.11	235.36	12.02	Rejected
Region-Specific,				
Boro Rice:				
Brahmanbaria	-30.53	0.126	12.02	Accepted
Dinajpur	-3.22	81.44	12.02	Rejected
Mymensingh	-24.19	19.58	12.02	Rejected
Aman Rice:				
Brahmanbaria	-2.23	102.18	12.02	Rejected
Dinajpur	-40.48	119.42	12.02	Rejected
Mymensingh	-26.59	86.58	12.02	Rejected

Source: Own estimation.

IV. CONCLUSIONS

Cobb-Douglas stochastic production frontiers were estimated for *Boro, Aus* and *Aman* 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 producton frontiers and technical inefficiency effect models were performed.

The stochastic production frontiers involve land, human labour, seed, fertilizer, manure, bullock power, irrigation cost, age of farm operator, experience of farm operator and extension service (dummy). All parameters in the crop-specific CobbDouglas stochastic production frontiers for all regions are significant except parameter of manure, and all of them have expected signs, with the exception of the parameter of education. The sign of the parameter of education variable is negative and significant which means that the rate of output decreases with the increase in education of farm operators. In other words, we can also say that less educated farmers are more productive than more educated farmers. Several reasons were identified to be responsible for the iaegative coefficient of education. Most of the educated farmers were found to have alternative income sources (service, business etc.) and they are not very much attentive with the farming practices and in that case they rely mostly on the fixed labourers those who have minimum education or no education at all. Another reason to include is that most of the educated farmers are village leaders and they were found to be busy with the problems of villagers and many of them were found to be engaged in local or national politics. The identified vital factors which are responsible for the increase of production are extension service, farm size, bullock power, age and experience. Seed, fertilizer and human labour and irrigation cost were identified as important factors for the increase of production for only *Boro* rice but they were not important factors fQr *Aus* and *Aman* rice crops. Slope parameters across equations are similar, which suggest that the frontier function represents a neutral upward shift of the OLS model (Table 2). The farm-specific technical efficiencies for *Boro* rice vary from 54% to 96% with mean technical efficiency 86%. Similarly, farm-specific technical efficiencies for *Aus* and *Aman* rice vary from 92% to 95% and 39% to 93% with average technical efficiency 93% and 80%, respectively.

The models for the technical inefficiency effects in the Cobb-Douglas stochastic production frontiers include age, education, experience, extension contact and farm size. Older farmers tend to have smaller inefficiencies than younger farmers. That is, technical efficiency increases with the increase in age of farmer. Education has no impact on the technical inefficiency effect. The coefficient of experience is significantly negative in the technical inefficiency effect models for all rice crops. That is, farmers with more experiences tend to have smaller technical inefficiencies (or greater technical efficiencies) than farmers with less experiences. Extension contact plays a vital role for the increase of technical efficiency of rice crops. Farmers with more extension contacts are technically more efficient than farmers with less extension contacts in all regions and in all farm size groups. Farm size has significantly negative effect on the technical inefficiency effect which indicates that the technical inefficiency effect decreases with the increase in farm size. We can also say that farmers with larger farms are technically more efficient than farmers with smaller operations. This contradicts the claim which is frequently made for developing country agriculture, that smaller farmers tend to be more efficient in production than larger farmers.

The variance ratio parameter γ associated with the variances in the single estimation of Cobb –Douglas stochastic production frontiers and the simultaneous estimation of Cobb-Douglas stochastic frontiers and technical inefficiency effect models is large and significant for all rice crops. It indicates that there are inefficiency effects in the production of all rice crops 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 farmers' levels of technical efficiency.

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