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Determinants of Technical Inefficiency of Rice Production in Groundwater Irrigation Markets in Bangladesh

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Abstract *The objective of this study is to determine the technical inefficiencies of rice production under different payment systems of irrigation. Forty eight upazilas were selected proportionately from the total rice areas of those five divisions. Unions, villages and household were selected randomly from the list of those. It is found that the technical efficiency and inefficiencies are different among the payment methods of irrigation. It is seen that the technical inefficiency is higher in share payment system which needs to be taken care for increasing production of HYV boro rice. Tabular model and graphic analyses show the same natures of the results that in the crop share payment system. The Tobit model shows the major determinants of those inefficiencies. The statistically significant factors are sandy loam soil type, education, kinship and asset position of the farmers. The sandy loam soil type has positive significant influence on technical inefficiency of HYV boro production. It is also seen that kinship and education level of the farmers have significant negative influence on technical inefficiency which are quit logical in the HYV boro rice production. Particularly it needs to emphasis the education level of the farmers since it is the highly significant factors for reducing inefficiency of rice production. Other than own payment system, cash payment is better in terms of efficiency consideration and two part tariff*

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payment system is the most feasible payment where farmers are less inefficient in producing HYV boro rice by using groundwater irrigation and the users have more freedom to use irrigation according to their crop needs. It can be also a situation where farmers will see the benefits of using AWD in their irrigation field. It will reduce irrigation cost and will also reduce the pressure of using groundwater irrigation in Bangladesh.

1. Introduction

The supply of rice, a staple food for half of the world's population and the primary source of income and employment of one-fifth of the global population, is strongly determined by small farmers' incentives for rice production. More than 200 million small farmers with an average of less than 1 hectare of land produce 90% of the total rice in the world (Tonini & Cabrera, 2011). Small farm households are believed to face a lower opportunity cost of labour than large farm households (Carter & Wiebe, 1990; Hunt, 1979; Sen, 1966). In Bangladesh, rice is the staple food of 149.8 million people and supplies 76% of the total calorie intake and more than 65% of the protein intake of the people (Dey, Miah, Mustafi, & Hossain, 1996). The agricultural sector is also characterized by the traditional subsistence small-scale farming. This country has shortage of all factors of production except labour, obviously cannot afford to make an inefficient use of resources. It is therefore important to estimate the level of technical efficiency at the farm-level, and to identify the sources of such efficiency and inefficiency. Information such as these are important for formulating appropriate policies for reducing the level of technical inefficiency. Measurement of technical efficiency could also help decide whether to improve efficiency first or develop a new technology in the short run. Technical efficiency is used as a measure of a farm's ability to produce maximum output from a given set of inputs under certain production technology.

Farm efficiency is examined by comparing the economic efficiencies of various types of farm holders (landless, marginal, small, medium and large). The majority of studies of agricultural productivity in developing countries support the view that there is an inverse relationship between productivity and farm size (Berry and Cline, 1979; Barrett, 1996). The relationship between farm size and efficiency is found to be non-linear, with efficiency first falling and then rising with size (Helfan et.al., 2004). High technical efficiency will not only enable farmers to increase the employment of productive resources, but it will also give a direction of adjustments required in the long run to increase food production. This present paper examines technical efficiency with emphasis on farm size in Bangladesh in order to suggest the ways to increase the levels of rice production in Bangladesh.

Previous studies in Asia have tested for relative efficiency differences by farm size, with conflicting results. Lau and Yotopoulos, 1971 and Yotopoulos and Lau, 1973 found that small wheat farms in the Indian Punjab were more technically efficient than large farms. In Pakistan, Khan and Maki (1979) found that large farms are more technically efficient than small farms. In Cote d'Ivoire, Adesina and Djato, 1996 found no differences in the technical efficiency of small and large farms. Onyenweaku, 1997 examined the technical efficiencies of two groups of farms in Kaduna state, Nigeria. The results showed higher level of technical efficiency for large scale farms. The above results on relative technical efficiency suggest the need to avoid generalizations in this regard as what obtains in one country may not follow in another country due to differences in agricultural and institutional settings. The definition of farm size has been variable in the efficiency literature, as what is considered "large" or "small" is relative depending on the agricultural system settings. In Pakistan agriculture, Khan and Maki, 1979 classified large farms as those having 12.5 acres or over 5 hectares. Using Indian data, Yotopoulos and Lau, 1973, and Sidhu, 1974 classified "large" farms as those with at least 10 acres (i.e., 4 ha). In Nigeria, Olayide et al., 1980 described small farms as those farm holdings less than 10 hectares. In a similar study in Cote d'Ivoire, Adesina and Djato, 1996 defined large farms as farms of at least 4 hectares. Ohajianya and Onyenweaku, 2002, in a similar study, defined large farms as farms of at least 4 hectares. In this study, large scale farmers were defined as farmers that have more than 3.04 ha (i. e.,7.50 acres) of land. This study investigates the productivity, technical inefficiency and their determinants among different rice farmers in Bangladesh. Necessary policies are suggested based on the findings of this study.

2. Methodology

A multi-staged sampling technique was employed to select a representative sample in this study. Five divisions were selected since they are the major rice growing divisions in Bangladesh. Forty eight upazilas were selected proportionately from the total rice areas of those five divisions. Unions and villages were selected randomly from the list of those. Then irrigated rice growing households were selected randomly. Based on the category of farm size, there were five categories of farmers identified. They were landless (<0.20 ha), marginal (0.20 – 0.40 ha), small (0.40 – 1.01 ha), medium (1.01 - 3.03 ha) and large (>3.04 ha) and their sample size were 17, 350, 357, 69 and 3 respectively. Data were collected using structured and validated questionnaire administered on the farm families using Surveybe CAPI software during the 2013 boro rice season by trained enumerators under the supervision of the researcher. Data were collected on the socioeconomic characteristics of the farmers, production activities in terms of inputs, outputs and their prices.

The methods to estimate farm household technical efficiency include parametric and nonparametric methods, i.e. stochastic frontier analysis (SFA) introduced by Farrell (1957) and data envelopment analysis (DEA) introduced by Charnes et al (1978). There are debates on which one is more appropriate approach for the technical efficiency estimation. DEA, the non-parametric approach, does not impose the restrictions the production function and distribution assumption of error terms and is suitable to deal with the multiple outputs (Chavas et al, 2005). However, the measurement errors can influence on the shape and positioning of the estimated frontier largely (Coeli and Battese, 1996). Instead, in SFA, the two error terms, i.e. technical inefficiency and random error term are specified explicitly (Coeli and Battese, 1996; Battese & Coelli, 1995). In this study, focus will be on only one single specific crop and SFA would be applied which is suitable for this research.

To apply SFA approach, it actually includes two regressions. The first one is to estimate the technical efficiency coefficient based on the input-output data at farm level by using production function and the second one is to evaluate the effects of determinants for inefficiency in different payment systems. It is proposed that one-stage regression is more appropriate than the two separate stage regression because the assumption of technical inefficiency coefficient is not hypothesized to be independent and affected by the covariates in the efficiency model (Battese and Coelli, 1995). One-stage approach is thus applied in the study, i.e. a stochastic production frontier based on the factors of production was estimated simultaneously with the determinants of inefficiency using maximum likelihood estimate following the methodology of Battese and Coelli (1995). We use here Tobit model since the technical inefficiency data are censored and its values are between 0 to 1.

2.1 Kernel Density Estimation (KDE)

In statistics, the univariate kernel density estimation (KDE) is a non-parametric way to estimate the probability density function f() of a random variable X, is a fundamental data smoothing problem where inferences about the population are made, based on a finite data sample. These techniques are widely used in various inference procedures such as signal processing, data mining and econometrics. It is used for estimating a density of probability and its derivatives with a bandwidth selector. The yield data in our survey supports the following distribution. This normal distribution of yield is useful to explain the inefficiency issue in different payment systems.

Technical efficiency and the determinants of technical inefficiency are calculated by first estimating a score for technical efficiency and then that score is used to

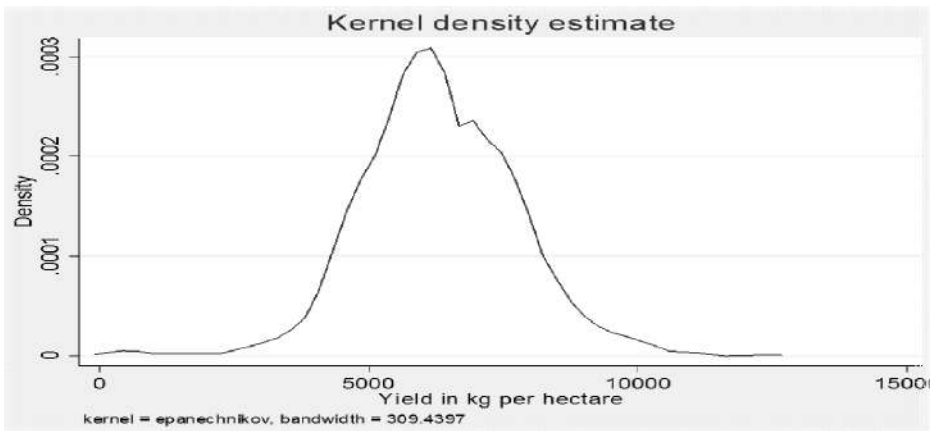


Figure 1. Kernel density estimation of yield

determine influencing factors. The output or yield of the stochastic production frontier is considered to be a function of input variables (Aigner et. Al., 1977). Following Coelli et al., 1998, a stochastic production function is specified as:

$Y_i = f(X_i) exp\ (5_i)$ ... ... *(1)*

Where Y_i is the yield for farmer i, X_i are the input variables used by the farmer i, 5_i is the error term, and f is the functional form to be specified. The error term is assumed to be composed of two separate errors, such that:

$5_i = v_i - u_i$ ... ...*(2)*

Where v_i is the stochastic error term with a two-sided noise component and u_i is the one-sided error component. Within the error term, v_i, accounts for random noise that is outside of the farmers' control as well as measurement errors. The second component, u_i, captures the absolute distance between farmers' yield and production possibility frontier. The first component, v_i is assumed to be normally distributed (v~N(0, σ^2_v) with a mean of zero and variance of σ^2_v. The second component, u_i is representing technical inefficiency (TI). If u=0, production lies on the stochastic frontier and production is technically efficient; if u>0, production lies below the frontier and is inefficient. Lastly, the two components of the error term are assumed to be independent of each other.

Farmers' individual technical efficiency scores are estimated to show the difference in the actual production to the potential production for each farm (Greene, 1980). The measurement of the technical efficiency is constructed using the observed deviation of output from individual farmers and the production frontier, the most efficient point obtainable by the farmers. Farmers with observed technical efficiency that lies on the production frontier are considered to be perfectly efficient. Conversely, any farmers with technical efficiency scores that are lying below the production frontier are considered to be technically inefficient. The index of technical efficiency is specified as:

$$\frac{Y_i}{f(X_i)e^{v_i}} = \exp(-\mu_i) \qquad (3)$$

Both descriptive and inferential statistics were used to analyze the pattern of inputs of production and the socioeconomic characteristics of the farm households. The Cobb-Douglas and Translog functional form will be used for this study. The empirical model of the Cobb-Douglas functional form (Gujarati, 1995) is as follows:

$$\ln Y_i = \beta_0 + \sum_{j=1}^{n} \beta_j \ln X_{ij} + v_i - \mu_i \qquad (4)$$

where:

ln	=	natural logarithmic form
Y_i	=	rice production (yield) in tons ha^{-1}
k	=	number of input variables
β_0	=	intercept or constant term
β_j	=	unknown parameters to be estimated
X_{ij}	=	vector of production inputs (j) of the farmer
v_i	=	random error term
u_i	=	inefficiency component

2.2 Translog production function

$$\ln Y_i = \beta_0 + \sum_{i=1}^{k} \beta_i \ln X_i + \frac{1}{2}\sum_{i=1}^{k}\sum_{j=1}^{k} \beta_{ij} \ln X_i \ln X_j + v_i - \mu_i \qquad (5)$$

We can generalized it in the following form like as,

$$\ln Y_i = \beta_0 + \beta_1 \ln X_{1i} + \beta_2 \ln X_2 i + 0.5\ \beta_{11}(\ln X_{1i})^2 + 0.5\ \beta_{22}(\ln X_{2i})^2 + 0.5\ \beta_{12} \ln X_{1i} \ln X_{2i} + v_i - \mu_i \qquad (6)$$

While the technical inefficiency model is given as:

$$\mu_i = \delta_0 + \sum_{i=1}^{k} \delta_{ij} Z_{ij} \quad \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots (7)$$

Where,

μ_i = technical inefficiency

δ_0 = intercept or constant term

δ_j = parameters to be estimated

Z_j = determinants of inefficiency

To determine the appropriate functional form for the model specification, a likelihood ratio test (LR test) is conducted. This test compares the translog function and the Cobb-Douglas. The null hypothesis is H_0: Cobb-Douglas

Table 1: Model selection test results

Hypothesis and decision	Criteria	LR value and probability
H0: Cobb-Douglas H1: Translog	Likelihood-ratio test (Assumption: Cobb_Douglas nested in Translog)	LR chi2(58) = 92.95 Prob > chi2 = 0.0024
Decision: Null hypothesis is rejected with ≤ 1 percent level of significance	Translog is the appropriate form for this data set.	

functional form and H1: Translog functional form. We run both the model and LR test as well. The test rejects the null hypothesis, H_0. This LR test proves that the translog functional form for estimating inefficiency with the current data set is the appropriate form of model.

Given a flexible and interactive production frontier for which the translog production frontier is specified, the farmer specific technical efficiency (TE) of the ith farmer is estimated by using the expectation of ui conditional on the random variable ei as shown by Battese (1992). That is, So that 0≤TE≤1. Farm specific technical inefficiency index (TI) is computed by using the following expression:

$$TE = \exp(-u_i) = e^{u_i} \ldots \ldots \ldots \ldots \ldots \ldots (8)$$

$$TI = [1 - \exp(-u_i)] \ldots \ldots \ldots \ldots \ldots \ldots (9)$$

In the production function, zero values were also observed in cases where farmers did not apply other fertilizer. As proposed by Battese (1997), the following methodology was applied to account for the zero values.

$$\ln Y_j = \beta_0 + (\alpha_0 - \beta_0) D_{2j} + \beta_1 \ln X_{1j} + \beta_2 \ln X_{2j} * + V_j, i = 1, 2, \ldots, n \quad \ldots \ldots \ldots (10)$$

where,

$D_{2j} = 1$ if $X_{2j} = 0$ and $D_{2j} = 0$ if $X_{2j} > 0$; and $X_{2j}^* = \text{Max}\ (X_{2j}, D_{2j})$

The model in equation 3 implies that $X_{2j}^* = X_{2j}$ is true for $X_{2j} > 0$ but if $X_{2j} = 0$ then $X_{2j}^* = 1$.

2.3 Empirical models specification: Cobb-Douglas

$$\ln Y_i = \beta_0 + \beta_1 \ln X_{1i} + \beta_2 \ln X_{2i} + \beta_3 \ln X_{3i} + \beta_4 \ln X_{4i} + \beta_5 \ln X_{5i} + \beta_6 \ln X_{6i} + \beta_7 \ln X_{7i} + \beta_8 \ln X_{8i} + \beta_9 \ln X_{9i} + \beta_{10} \ln X_{10i} + \beta_{11} \ln X_{11i} + v_i - \mu_i \quad \text{.. ... ...} \quad (11)$$

Where,

Y_i = Yield (kg)

X_{1i} = Seed (kg/ha)

X_{2i} = Human labour (man-day/ha)

X_{3i} = Tillage (hour/ha)

X_{4i} = Irrigation (hour/ha)

X_{5i} = Chemical fertilizer (kg/ha)

X_{6i} = Insecticide & herbicides (kg or lit/ha)

X_{7i} = Other fertilizer dummy (1=use other fertilizer, 0= otherwise)

X_{8i} = Other cost dummy (1=use other cost, 0=otherwise)

X_{9i} = Share payment dummy (1=under share payment, 0=otherwise)

X_{10i} = Fixed charge dummy (1=under fixed charge payment, 0=otherwise)

X_{11i} = Two part dummy (1=under two part tariff payment, 0=otherwise)

We have used own payment system as reference case.

β_0 = Constant term,

β_{1-11} = Unknown parameters to be estimated from the Cobb-Douglas production function

ξ_i = Error term

2.4 Empirical models specification: Translog

$$\ln Y_i = \beta_0 + \beta_1 \ln X_{1i} + \beta_2 \ln X_2 i + 0.5\ \beta_{11} (\ln X_{1i})^2 + 0.5\ \beta_{22} (\ln X_{2i})^2 + \beta_{12} \ln X_{1i} \ln X_{2i} + \ldots + v_i - \mu_i \quad \text{.................... ....} \mathit{(12)}$$

2.5 Censored data distribution

A very common problem in microeconomic data is censoring of the dependent variable. When the dependent variable is censored, values in a certain range are all transformed to a single value range. Some examples that have appeared in the empirical literature are household purchases, farm experimental affairs, hours worked by women in farms and industries, household expenditure on various commodities, etc. Each of these studies analyzes a dependent variable that is zero for significant fraction of the observations. Conventional regression methods fail to account for the quantitative difference between limit (zero) observations and non-limit (continuous) observations. The relevant distribution theory for a censored variable is similar to that for a truncated one. We begin with the normal distribution, as much of the received work has been based on an assumption of normality. We also assume that the censoring point is zero, although this is only a convenient normalization. In a truncated distribution, only the part of distribution above y=0 is relevant to our computations. To make the distribution integrate to one, we scale it up by the probability that an observation in the un-truncated population fails in the range that interests us. When data are censored, the distribution that applies to the sample data is a mixture of discrete and continuous distribution. To analyze this distribution, we can define a new random variable y transformed from the original one, y^*, by

$$y = 0 \text{ if } y^* \leq 0$$

$$y = y^* \text{ if } y^* > 0$$

The distribution that applies if $y^* \sim N[\mu, \sigma^2]$ is Prob(y=0) = Prob($y^* \leq 0$) = ξ ($-\mu/\sigma$) = $1-\xi$ (μ/σ), and if $y^* > 0$, then y has the density of y^*. This distribution is a mixture of discrete and continuous parts. The total probability is one, as required, but instead of scaling the second part, we simply assign the null probability in the censored region to the censoring point, this case, zero (Greene, 2006).

2.6 Tobit model setup

Wooldrige (2002, 517-520) makes clear, censored regression applications fall into two categories. They are: 1. Censored regression application, and 2. Corner solution models. Both types of application- the censored regression application and corner solution application lead us to the standard censored Tobit model with type-1 (Sigelman and Zeng, 1999).

The structural equation in Tobit model (Tobin, 1958) is $Y^*_i = X_i\beta + \xi_i$ Where ξ $i \sim N(0, \sigma^2)$. Y^* is a latent variable that is observed for values greater than τ and

Table 2: List of variables and interaction factors are as follows

Input variables	**Interaction factor variables**
1. Seed	12. 0.5*Seed^2, 13. Seed*Human labour, 14. Seed*Tillage, 15. Seed*Irrigation, 16. Seed*Chemical fertilizer, 17. Seed* Insecticide & herbicides, 18. Seed* Other fertilizer dummy, 19. Seed* Other cost dummy, 20. Seed* Share payment dummy, 21. Seed* Fixed charge dummy, 22. Seed* Two part dummy
2. Human labour	23. 0.5*Human labour^2, 24. Human labour*Tillage, 25. Human labour*Irrigation, 26. Human labour*Chemical fertilizer, 27. Human labour*Insecticide & herbicides, 28. Human labour*Other fertilizer dummy, 29. Human labour*Other cost dummy, 30. Human labour*Share payment dummy, 31. Human labour* Fixed charge dummy, 32. Human labour*Two part dummy
3 . Tillage	33. 0.5*Tillage^2, 34. Tillage*Irrigation, 35. Tillage*Chemical fertilizer, 36. Tillage*Insecticide & herbicides, 37. Tillage* Other fertilizer dummy, 38. Tillage*Other cost dummy, 39. Tillage* Share payment dummy, 40. Tillage*Fixed charge dummy, 41. Tillage* Two part dummy
4. Irrigation	42. 0.5*Irrigation^2, 43. Irrigation* Chemical fertilizer, 44. Irrigation* Insecticide & herbicides, 45. Irrigation*Other fertilizer dummy 46. Irrigation*Other cost dummy, 47. Irrigation* Share payment dummy, 48. Irrigation*Fixed charge dummy, 49. Irrigation* Two part dummy
5. Chemical fertilizer	50. 0.5*Chemical fertilizer^2, 51. Chemical fertilizer*Insecticide & herbicides, 52. Chemical fertilizer*Other fertilizer dummy, 53. Chemical fertilizer*Other cost dummy, 54. Chemical fertilizer* Share payment dummy, 55. Chemical fertilizer* Fixed charge dummy, 56. Chemical fertilizer* Two part dummy
6. Insecticide & herbicides	57. 0.5*Insecticide & herbicides^2, 58. Insecticide & herbicides* Other fertilizer dummy, 59. Insecticide & herbicides*Other cost dummy, 60. Insecticide & herbicides* Share payment dummy, 61. Insecticide & herbicides* Fixed charge dummy, 62. Insecticide & herbicides* Two part dummy
7. Other fertilizer dummy	63. Other fertilizer dummy*Other cost dummy, 64. Other fertilizer dummy*Share payment dummy, 65. Other fertilizer dummy*Fixed charge dummy, 66. Other fertilizer dummy*Two part dummy
8. Other cost dummy	67. Other cost dummy*Share payment dummy, 68. Other cost dummy* Fixed charge dummy, 69. Other cost dummy*Two part dummy
9. Share payment dummy	-
10. Fixed charge dummy	-
11. Two part dummy	-

censored otherwise. The observed y is defined by the following measurement equation

$$y_i = \begin{cases} y^* \text{ if } y^* > \tau \\ \tau_y \text{ if } y^* \leq \tau \end{cases}$$

In the typical Tobit model, we assume that $\tau = 0$ i.e. the data are censored at 0. Thus, we have

$$y_i = \begin{cases} y^* \text{ if } y^* > 0 \\ 0 \text{ if } y^* \leq 0 \end{cases}$$

Marginal effects for Tobit model is

$$\frac{\delta E[y^*]}{\delta x_k} = \beta_k \dots \dots \quad \dots \dots (8)$$

Thus the reported Tobit coefficients indicate how a one unit change in an independent variable x_k alerts the latent dependent variable.

It is important to realize that estimates the effect of x on y^*, the latent variable, not on y. The Tobit model depends on the correctness of the normality assumption. The interpretation of the parameters becomes more difficult than in the linear model. We need to compute partial effects of changing x as we have done for the Logit and Probit model. These partial effects depend not only on β but also on x and σ. Stata 12 version can carry out these calculations automatically.

Empirical model for the determinants of technical inefficiency

$$\ln Y_i = \beta_0 + \beta_1 \ln X_{1i} + \beta_2 \ln X_{2i} + \beta_3 \ln X_{3i} + \beta_4 \ln X_{4i} + \beta_5 \ln X_{5i} + \beta_6 \ln X_{6i} + \beta_7 \ln X_{7i} + \beta_8 \ln X_{8i} + \beta_9 \ln X_{9i} + \beta_{10} \ln X_{10i} + \mu_i \quad \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots\dots \dots \textit{(13)}$$

Where,

Y_i = Technical inefficiency [Censored values, ll(o) & ul(1)]
X_{1i} = Sandy loam soil type dummy (1=sandy loam soil, 0=otherwise)
X_{2i} = Clay loam soil type dummy (1=clay loam soil, 0=otherwise)
X_{3i} = Clay soil type dummy (1=clay soil, 0=otherwise)
X_{4i} = Medium high land type dummy (1=medium high land, 0=otherwise)
X_{5i} = high land type dummy (1=high land, 0=otherwise)
X_{6i} = Farm size (ha)
X_{7i} = Kinship dummy (1=kinship, 0= otherwise)
X_{8i} = Family head age (year)
X_{9i} = Family head education (year of schooling)

X_{10i} = Distance from plot to tubewell (meter)
X_{11i} = Asset position of the farmer (Tk.)
X_{12i} = Loan dummy (1=loan receiver, 0=otherwise)
μ_i = Error term

3. Results discussion

The generalized likelihood ratio test is used here which is commonly used in stochastic frontier analysis to determine the appropriate functional form (Battese and Coelli 1988, 1992 Coelli 1995, Battese and Hassan 1998). We use a procedure to determine the functional form. We test the null hypothesis that Cobb-Douglas half normal is nested under the translog half normal function. We fail to reject the null hypothesis. We estimate equation (5) using the translog half normal function. The estimate of the stochastic frontier shows the best practice performance of HYV boro production under the available technologies which was first represented by a production function, such as Cobb-Douglas and constant elasticity of substitution (CES) place restriction on elasticity of substitution (Cobb and Douglas, 1928; Arrow, et al. 1961). The model goodness of fit is well with the correctness of the specified distributional assumptions. Here log likelihood is -9.75 and Wald chi-squared at 69 degrees of freedom is 121.52 which are significant at less than 1 percent level of significant. LR test of sigma_u=0 i.e. probably testing whether an estimated variance component (something that is always greater than zero) is different from zero. The test says it is significantly different from zero at less than 1 percent level of significance. The mean value of technical efficiency is 0.77 is higher than 0.75, 0.62, 0.47 found by Kumbhakar (1994), Huaiyu, et al., (2012) and Al-hasan, (2012) respectively. Our technical efficiency level is lower than 0.83, 0.96, and 0.89 which were found by Huang & Bagi (1984), Parikh & Shah (1994), Tadesse & Krishnamoorthy (1997), respectively.

The variables those have significant influences on yield are two part payment dummy, seed-tillage, seed-irrigation, seed-two part payment dummy, labour-irrigation, labour-chemical fertilizer, tillage, tillage-other fertilizer, tillage-two part payment dummy, irrigation other fertilizer, irrigation-share payment dummy and chemical fertilizer-other fertilizer dummy. Most of the coefficients of those variables or interactive factors are significant at 1 & 5 percent level of significance. Different cross product or interaction factors have robust influence on yield which means the interaction factors need to be taken care intensively to explain the yield variation of the farmers. Irrigation and tillage have linked with payment system and it seen that the share crop payment dummy has significant negative influence on technical efficiency of HYV boro rice production.

Interpretation of Technical Efficiency and inefficiency Scores

Computationally, the technical efficiency scores relate to the distance of a farmer's current production point from its respective benchmarking frontier of

Table 3: List of significant variables in the translog model

Number of observation =958
Wald chi-square =121.52
Probability > chi-square = 0.0001
Log likelihood = -9.745668

Input variables and integration variables	Coefficient.	Std. Err.	z	P>z
Two part dummy	-1.028**	0.437	-2.350	0.019
Seed-tillage	-0.080***	0.027	-2.960	0.003
Seed-irrigation	0.033**	0.016	2.000	0.046
Seed-two part tariff dummy	0.057*	0.032	1.780	0.075
Labour-irrigation	0.076**	0.037	2.090	0.037
Labour-chemical fertilizer	0.112**	0.068	1.640	0.102
Tillageha^2	-0.063*	0.038	-1.640	0.101
Tillage-other fertilizer	-0.099**	0.037	-2.700	0.007
Tillage-two part tariff dummy	0.130***	0.046	2.820	0.005
Irrigation-other fertilizer	-0.039*	0.022	-1.780	0.074
Irrigation-share payment dummy	-0.069**	0.034	-2.050	0.040
Chemical fertilizer-other fertilizer	0.107**	0.050	2.150	0.031
Constant term	12.232	1.633	7.49	0.00
/lnsig2v	-4.374	0.159	-27.560	0.000
/lnsig2u	-1.888	0.073	-25.940	0.000
sigma_v	0.112	0.009	-	
sigma_u	0.389	0.014	-	
sigma2	0.164	0.010	-	
lambda	3.466	0.020	-	
Likelihood-ratio test of sigma_u=0: chibar2(01) = 2.3e+02Prob>=chibar2 = 0.000				

*, **, *** significant at 10%, 5% and 1% level of significance

HYV rice production. The exact interpretation is specific to the model orientation. For the output oriented model, the efficiency scores measure the volume of output that a farmer is currently producing, relative to the maximum volume it could potentially produce from its current inputs. For example, an output-oriented efficiency score of 77 per cent would mean that a farm is producing 77 per cent of its full output potential. This would be interpreted to mean that the farmer is producing at 23 per cent below its maximum capacity or that it has the potential to increase its current output level by 23 per cent without needing to increase its resources. This 23 is nothing but the technical inefficiency score of a HYV rice producing farmer.

3.1 Division-wise inefficiency level

Inefficiency levels are also presented at different divisions of Bangladesh. It is seen that the inefficiency is higher at own payment system in Chittagong division. Average inefficiency is the lowest in two part payment system in Rajshahi division and it is followed by the Khulna division. In Rangpur division, we do not have information about share payment system. Still the average inefficiency is lower in crop share system.

Table 4: Division-wise technical efficiencies and inefficiencies of the farmers under different payment systems

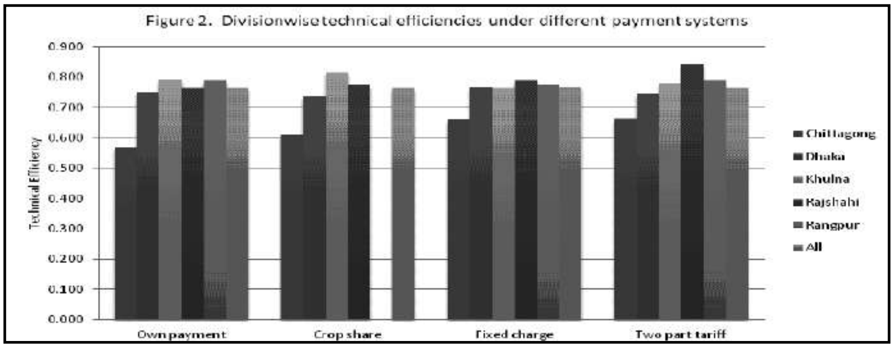
Division name	Technical efficiency level				Technical inefficiency level			
	Own payment	Crop share	Fixed charge	Two part tariff	Own payment	Crop share	Fixed charge	Two part tariff
Chittagong	0.568	0.609	0.661	0.662	0.432	0.391	0.339	0.338
Dhaka	0.750	0.736	0.769	0.745	0.250	0.264	0.231	0.255
Khulna	0.793	0.818	0.768	0.780	0.207	0.182	0.232	0.220
Rajshahi	0.765	0.774	0.792	0.844	0.235	0.226	0.208	0.156
Rangpur	0.792	0.000	0.773	0.791	0.208	0.000	0.227	0.209
All	0.767	0.763	0.768	0.766	0.233	0.237	0.232	0.234

3.2 Overall technical inefficiency level

The inefficiency levels of the farmers are higher between the ranges of 0.1 to 0.4. Most of the farmers (52%) are between 0.1 to 0.4 inefficiency levels. It can be mentioned here that magnitudes of the inefficient farmers are lower and also means that they not so far from technically efficient farmers.

Inefficiency level under different payment systems

It can be seen that the distribution of inefficiencies are different among the payment systems. The range is lower in share payment system but higher



inefficiency lies on that payment method. In two part tariff payment system, most of the farmers have lower inefficiency. The patterns are similar in fixed payment system.

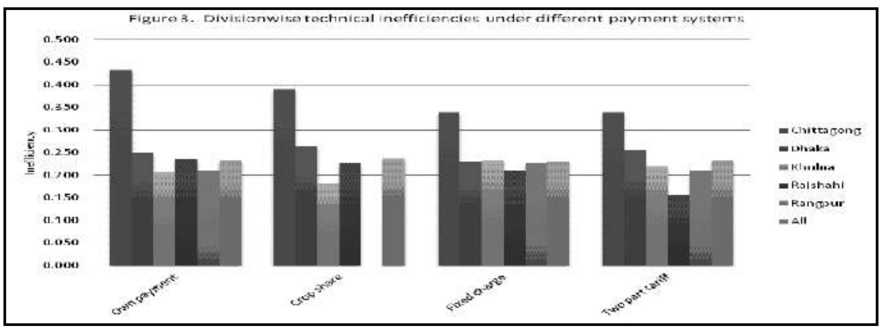
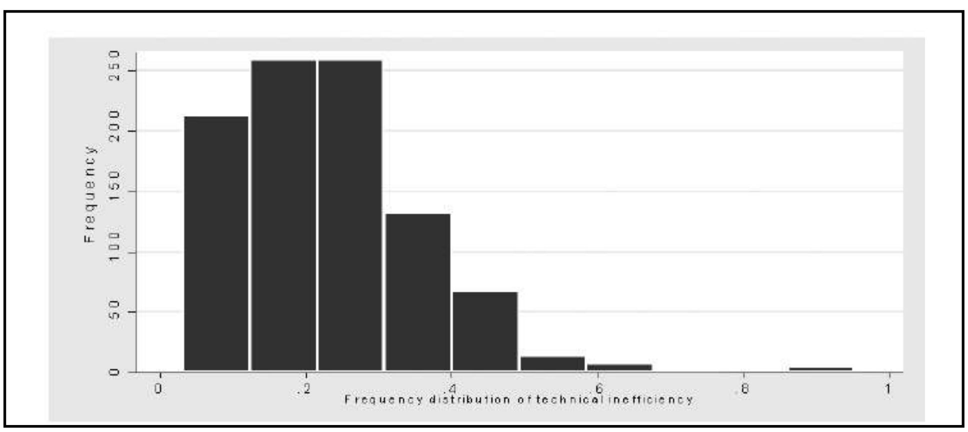


Figure 4. Frequency distribution of technical inefficiency



Ranking of inefficiency in different payment systems

The following table shows that the technical efficiency ranking is the lowest in share payment system of irrigation but the highest in fixed charge system and it is

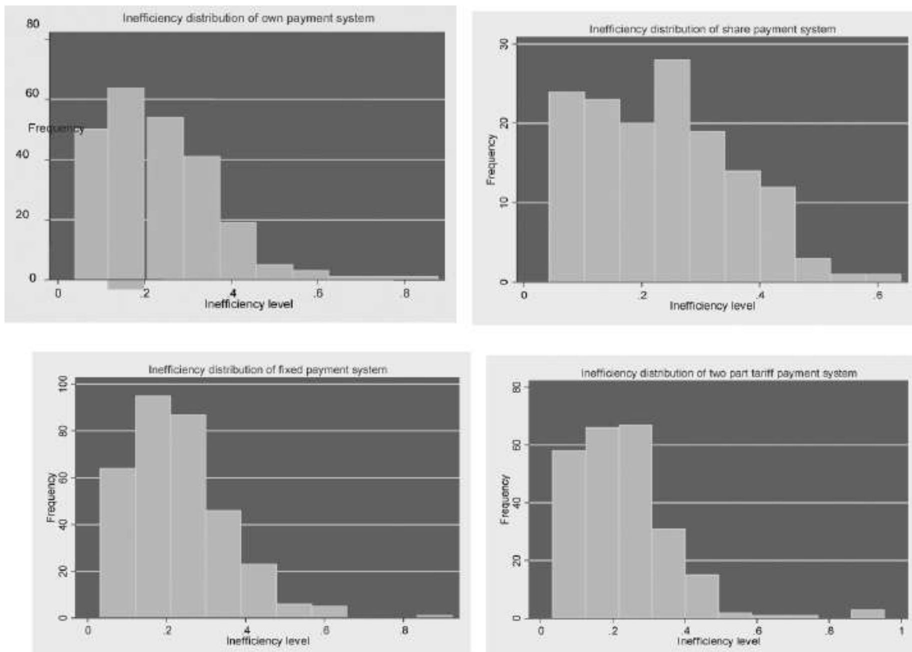


Figure 5. Frequency distribution of technical inefficiency in different payment systems

Table 5: Technical efficiency, inefficiency and rank under different payment systems

Payment methods	Technical efficiency	TE Rank	Technical inefficiency	TI Rank
Own payment	0.767	2	0.232	3
Crop share	0.763	4	0.237	1
Fixed charge	0.768	1	0.231	4
Two part tariff	0.766	3	0.234	2
All	0.767	-	0.233	-

because of the efficient inputs use other than irrigation by the users. Due to the same reason, the TE is higher in own payment system. We can see almost the opposite scenario in inefficiency ranking in different payment systems. Technical inefficiency in crop share payment system is the highest in ranking among other payment systems (Table 3).

Socioeconomic influence on HYV rice production inefficiency

A total of ten socioeconomic and farm characteristic variables are investigated as the determinants of technical inefficiency. There are four major soil types are

Figure 6. Technical efficiencies in different payment systems

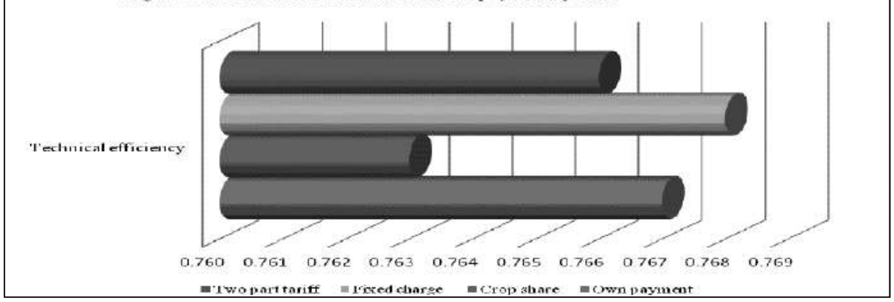
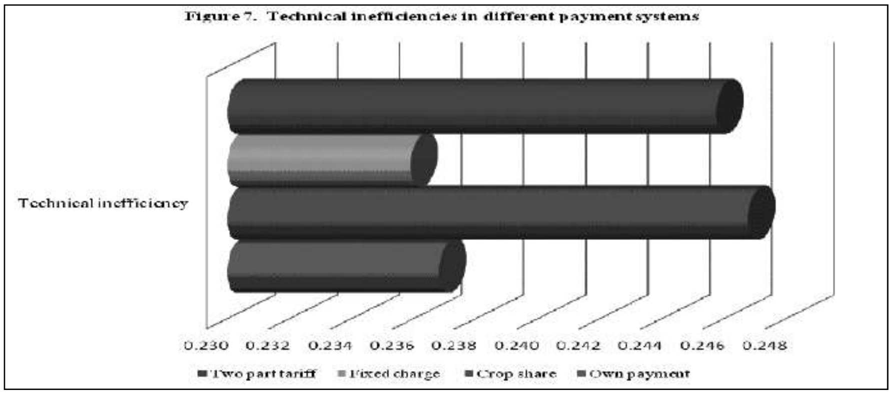


Figure 7. Technical inefficiencies in different payment systems



mentioned by the farmers where they grow HYV boro rice. Three dummies are taken to capture four types of soil. As before, loam soil is the reference soil type. The dummies are sandy loam soil, clay loam soil and clay soil. Loam soil type is

Table 6: Determinants of technical inefficiency in irrigated HYV boro rice by using Tobit model

Determinants of inefficiency	Coefficients	Std. Err.	t	P>t
Sandy loam soil type dummy	0.0209**	0.0105	1.99	0.047
Clay loam soil type dummy	0.0163	0.0132	1.23	0.219
Clay soil type dummy	-0.0058	0.0115	-0.51	0.611
Medium high land type dummy	0.0121	0.0091	1.33	0.185
High land dummy	0.0082	0.0134	0.62	0.538
Farm size (ha)	-0.0068	0.0066	-1.03	0.301
Respondent's age	0.0162	0.0153	1.06	0.29
Respondent's education	-0.0128***	0.0046	-2.78	0.006
Kinship dummy	-0.0178*	0.0095	-1.88	0.061
Distance from plot to tubewell	0.0021	0.0024	0.89	0.373
Asset position of the farmer	-0.0083*	0.0049	-1.7	0.089
Loan dummy	0.0003	0.0084	0.03	0.975

*, **, *** significant at 10%, 5% and 1% level of significance

captured by the constant term. It is determined that sandy loam soil type has positive significant influence on technical inefficiency of HYV boro production. It is seen that education of the respondent, kinship and asset position of the farmers have significant negative influence on technical inefficiency which are quit logical in the practical situation. Here respondent's education is highly significant meaning is that we need to take special care for education to reduce the technical inefficiency in producing HYV boro rice and it can increase our yield more.

4. Conclusions

It is found that the efficiency varies among the payment systems of irrigation water. Also technical efficiency and inefficiencies are different among the payment methods of irrigation. Technical inefficiency is higher in share payment system which needs to be taken care for increasing production of HYV boro rice. Tabular model and graphic analyses show the same natures of the results that the crop share payment system. The Tobit model shows the major determinants of those inefficiencies. The statistically significant factors are sandy loam soil type, education, kinship and asset position of the farmers. The sandy loam soil type has positive significant influence on technical inefficiency of HYV boro production. It is also seen that kinship and education of the farmers have significant negative influence on technical inefficiency which are quit logical in the HYV boro rice production. Particularly we need to emphasis the education level of the farmers since it is the highly significant factors for reducing inefficiency of rice production. Other than own payment system, cash payment is better in terms of efficiency consideration and two part tariff payment system is the most feasible payment where farmers are less inefficient in producing HYV boro rice by using groundwater irrigation and the users have more freedom to use irrigation according to their crop needs. It can be also a situation where farmers will see the benefits of using AWD in their irrigation field. It will reduce irrigation cost and will also reduce the pressure of using groundwater irrigation in Bangladesh.