Do differences in technical efficiency explain the adoption rate of HYV rice? Evidence from Bangladesh

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Abstract

This paper estimates the technical efficiency of traditional variety (TV) and high-yielding-variety (HYV) rice producers in Bangladesh as well as explores the determinants of HYV rice adoption in a survey data from 360 farmers for the 2008/09 growing seasons. Estimates by stochastic frontier analysis indicated that in spite of its much yield potential, HYV rice production was associated with lower technical efficiency and had a greater variability in yield. Results indicated that technical efficiency of HYV and TV rice were related to age, experience, off-farm income, extension visits, and access to microfinance. A Tobit analysis revealed that the adoption of HYV rice was significantly and positively influenced by farmers' age and experience, level of technical efficiency, irrigation coverage, off-farm incomes, access to microfinance, perception of yield and membership of village-local groups.

Keywords: *Traditional variety, High-yielding-variety, Stochastic Frontier Analysis, Adoption, Tobit Analysis.*
JEL Classification: *N5, Q12.*

Introduction

Bangladesh, a country of 140.6 million people (BBS, 2008), is predominately an agrarian economy in which agricultural growth is considered as the key to rural socio-economic development in general and the development of the whole country in particular. The agricultural sector of Bangladesh has diminished in terms of its share in gross domestic product (GDP) and labour force employed over the past decade. However, agriculture still accounts for 21% of GDP and 50% of overall employment in Bangladesh (Bangladesh Agricultural Census, 2008). The main food crop of Bangladesh is rice, which accounts for 94% of the cereals consumed and provides 68% of the protein in the national diet. Rice also accounts for approximately 78% of the value of agricultural output, and 30% of consumer spending (Ahmed and Haggblade, 2000). As much as 94% of all the crops produced (Bangladesh Economic Review, 2009), and 77% of the cropped area in Bangladesh is devoted to rice cultivation (BBS, 2006). Three rice crops are grown during the crop cycle beginning in April - the 'Aus' (spring) crop, the 'Aman' (summer) crop, and the 'Boro' (winter) crop. The first two are traditional, rain-fed crops, whereas the Boro crop is the Higher Yielding Variety (HYV). In spite of the major contribution of rice to the agricultural sector of the economy, many traditional rice producers are incapable of producing at the frontier level to contribute to food

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security and satisfy household consumption. Thus for a land scarce country such as Bangladesh in which the agriculture sector already operates at its land frontier, an increase in food production can only arise from the widespread acceptance and implementation of modern agricultural technologies (Azam, 1996). The 'Green Revolution' involves the adoption of HYV rice varieties and the use of fertilisers and irrigation (Bray, 1986). The benefits of the of widely accepted shorter-duration HYV rice are their capacity to produce higher yields and returns per unit of land compared to TVs and also their lower vulnerability to flood effects as they grow in winter. Moreover, government policies encourage the adoption of HYV rice through the measures like seed market reform, soil improvement, the availability of irrigation water, fertiliser subsidies and other inputs, along with adaptive research and extension. These measures ensure clear advantages to the adoption HYV rice. However, the adoption of HYV rice in Bangladesh is lowest compared to other Asian countries (Bera and Kelley, 1990) and it only accounts for 38.6% of the total rice area (BBS, 2006).

Even with the introduction of the 'Green Revolution' in Bangladesh in 1968, the yields of rice per hectare of land remain low. The average rice yield in Bangladesh is 2.74 tonnes/ha (BBS, 2008) which is much lower than those of other Asian countries. Consequently, the potential gain from closing the yield gap in Bangladesh is higher than those for China, Korea, Indonesia, Myanmar, Nepal and Vietnam (Pingali et al., 1997). In an effort to maintain productivity growth, the Bangladesh Rice Research Institute (BRRI) has developed over 30 HYVs for different seasons and agro-ecological zones. Moreover, over the past four decades, the major thrust of national policy has been directed towards the acceptance of improved varieties of rice through the greater use of chemical inputs and fertilisers in Bangladesh (Mendola, 2007). Despite the obvious potential significance of these measures, little is known about the attitudes of Bangladeshi farmers towards the adoption of HYV rice. Accurate information about the perception of farmers of HYV rice varieties, the socio-economic factors affecting their decision to adopt HYV and the efficiency of HYV production itself are essential factors to exploit optimal benefits of HYV rice.

The aims of this study are twofold. The first objective is to find out whether there are significant differences in technical efficiency of production between traditional local varieties and HYV rice. This would give some indications about the efficient use of resources in the event of opting for more HYV and less TVs. The second aim is to identify the factors that contribute towards the adoption of HYV rice. Several factors that affect the adoption of HYV crops were reported in empirical studies (Sall et al., 2000; Ransom et al., 2003; Azam, 1996; Shiyani, 2002). However, very little is known about how the differences in technical efficiency affect the adoption of HYV rice. Therefore, the empirical question to be answered in this study is whether differences in technical efficiency can explain the adoption rate of HYV rice.

The rest of the paper is organized as follows: section 2 presents a brief review of the frontier function methodology, section 3 describes the data and variables along with the empirical model, section 4 presents the estimation results, and section 5 ends the paper with a set of concluding remarks.

Analytical Framework

Stochastic production frontier

Farrell's (1957) seminal paper on efficiency measurement led to the development of several methodologies and approaches to efficiency and productivity analysis. Stochastic frontier analysis (SFA) and Data envelopment analysis (DEA) are the two pioneering contributions in this field. Aigner et al. (1977), and Meeusen and Van Den Broeck (1977) independently proposed the stochastic frontier production function with a composed error term including a stochastic error component and one-sided error component representing technical inefficiency of production. DEA was approached by Charnes *et al.*(1978). The advantages and disadvantages of each have been discussed by Coelli and Perelman (1999). The popular approach to measure the technical efficiency is frontier production function (Tzouvelekas et al., 2001; Wadud and White, 2000; Sharma et al., 1999; Battese and Coelli, 1995).

The factors influencing technical efficiency have been analyzed in several studies (Nyemeck et al., 2003; Bravo-Ureta and Pinheiro, 1997) by a second stage regression after the estimation of efficiency scores. This approach contains serious problems regarding the assumptions made for the non-negative random variable, u_i. Moreover, the second stage specification conflicts with the assumption that u_is are independent and identically distributed. However, a number of authors (Kumbhakar et al., 1991; Battese and Coelli, 1995) modified and extended the stochastic production frontier model by suggesting a simultaneous estimation of the production frontier and inefficiency effects. They argued for a single stage approach by which the functional relationship between inefficiency effects and the firm-specific factors are directly incorporated into the Maximum Likelihood Estimation (MLE). Following Battese and Coelli (1995), the following stochastic frontier production function and inefficiency effects model can be estimated simultaneously in a single stage by using the computer program, FRONTIER 4.1, developed by Coelli (1996). Using their specification, the technology of a decision-making unit (DMU) i (a firm) is represented by a stochastic production frontier as follows:

$$Y_i = f(X_i;\beta) + \varepsilon_i \qquad i = 1, 2, ..., N \tag{1}$$

where, Y_i denotes the revenue from rice for the i^{th} DMU; $X_i = (x_{i1}, x_{i2}, ..., x_{ik})$ is a vector of k inputs (or cost of inputs), β is a vector of unknown parameters to be estimated, $f(\cdot)$ is a suitable functional form for the frontier (Cobb-Douglas, translog or quadratic), ε_i is the composite error term, and N is the number of DMUs. The ε_i term was defined in two studies (Aigner et al., 1977; Meeusen and Van den Broeck 1977) as follows.

$$\varepsilon_i = v_i - u_i \text{ , } (i = 1, 2, ..., N) \tag{2}$$

where v_i are assumed to be independently and identically distributed (*i.i.d*) random errors that capture the stochastic effects outside the control of the farmers under the distribution $v_i \sim iid\ N\ (0, \sigma_v^2)$, which are independent of the u_is. Thus, v_i, allow the production frontier to vary across farms, or over time for the same farms and therefore, the production frontier is stochastic in nature. The term u_i (asymmetric non-negative error term) is a one sided ($u_i \geq 0$) efficiency component that captures the technical inefficiency of the i^{th} farm and is assumed to be *i.i.d* and truncated (at zero) under the normal distribution with a mean of μ, and a variance $\sigma_u^2 \left(\left|N(\mu, \sigma_u^2)\right|\right)$. This may follow a half-normal, exponential, truncated-normal or gamma distribution (Stevenson, 1980; Aigner et al., 1977; Meeusen and Broeck, 1977). The variance parameters of the model are parameterized as:

$$\sigma_s^2 = \sigma_v^2 + \sigma_u^2, \gamma = \sigma_u^2 / \sigma_s^2 \quad \wedge\ 0 \leq \gamma \leq 1 \tag{3}$$

Here, σ_s^2 denotes the total variation in the dependent variable due to an aggregate of technical inefficiency (σ_u^2) and random shocks (σ_v^2). The gamma (γ) parameter explains the impact of inefficiency on output. The MLE for equation (1) provides consistent estimators for β, γ, and σ_s^2 parameters. The parameter γ must lie between 0 and 1. A value of γ close to zero implies that much of the variation of the observed output from frontier output is due to random stochastic effects. If the value of γ is close to one it implies that most of the random variation in output is explained by inefficiency effects or differences in technical efficiency.

Quantifying factors affecting adoption of HYV rice

Rogers (1962) defined adoption as 'the mental process an individual passes through from first hearing about an innovation to final adoption'. Final adoption at the farm level is defined as the use of new technology in the long-run equilibrium, and assumes that the farm has full information about the new technology and it's potential. However, if the innovation is modified periodically, the equilibrium level may not be reached. The literature also distinguishes between 'rates of adoption' and the 'intensity of adoption'. The former determines the proportion of farmers who adopt a given technology regardless of the level of use, and the latter determines the level of use of that technology such as the proportion of land planted under HYVs or the quantity of fertiliser used. The adoption process starts with farmers experimenting with new varieties, which may lead them to select that new variety if its performance is viewed by the farmer as superior over those of traditional varieties (Shiyani et al., 2002).

In the present study, taking into account the non-awareness bias, we used a censored regression Tobit model (Tobin, 1958) in which the sample population consists of both the adopters and non-adopters of HYV boro rice. The rationale behind using the Tobit model is its bounded nature in that the observed values of the dependent variable has a limited range (0 and 1). Another rational of this model is that it permits the measurement of probability of adoption of an improved variety in addition to the intensity of adoption[1] (Adesina and Zinnah, 1993). In Bangladesh, farmers who adopt HYV rice generally plant their entire land holdings under HYV rice, so the intensity measure can take a value of either 0% or 100%. When this is the case the rate of the adoption measure approximates to that of the intensity of adoption measure (Doss and Morris, 2001). In view of this similarity the present study focuses on the intensity of adoption of HYV rice as measured by the percentage of total rice area planted under HYV rice in Bangladesh. The general expression is usually given in terms of an index function defined as the following:

$$y_i = x_i b + \varepsilon_i ,\ \text{if}\ y_i^* = x_i b + u_i > 0 ,\ \text{or}\ y_i = 0\ \text{if}\ y_i^* = x_i b + u_i < 0 \quad (4)$$

where, y_i is the index function that represents the probability of adoption and the intensity of adoption of HYV Boro rice; y_i^* is a non-observable latent variable; b is a $kx1$ vector of parameters to be estimated and u_i~iid N (0, σ_u^2). The MLE method is used to estimate the parameters in equation (4).

The Empirical Models

Model 1: Stochastic frontier production function

The results of the likelihood ratio test, used to test the Cobb-Douglas functional form against the translog functional form, showed that the Cobb-Douglas function was an appropriate model for our data. Consequently, we used the Cobb-Douglas production function to estimate the technical efficiency for the rice farmers in Bangladesh. Moreover, regarding the impact of functional form on efficiency, Kopp and Smith (1980) concluded "…that functional specification has a discernable but rather small impact on estimated efficiency." For this reason the Cobb-Douglas functional form has been widely used in farm efficiency analysis in developing and developed countries (Battese, 1992; Bravo-Ureta and Pinheiro, 1993; Binam et al., 2004). Therefore, the following stochastic frontier production function and inefficiency effects model was estimated using a single stage by using the computer program, FRONTIER 4.1, developed by Coelli (1996)

$$\ln Y_i = \ln \beta_0 + \sum_{j=1}^{7} \beta_j \ln \mathrm{X}_{ij} + \varepsilon_i \qquad (5)$$

where, Y_i denotes the value of Aus/Aman/Boro rice produced by i^{th} farm and is measured in Taka; X_j are the j^{th} input used and; *ln* = natural logarithm; j = 1, denotes the total land under each crop in hectares; j = 2, denotes the total of family and hired labour in man-days for each rice crop; j = *3, 4, 5, 6, 7* represent the expenditures for seed, fertilisers, irrigation, tilling and other variable costs for each crop during the growing season. All expenditures were expressed in Taka.

Following, Battese and Coelli (1995), we assume the distribution of technical inefficiency (u_i) effect is related to farmers' socio economic and management factors and is expressed as follows:

$$u_i = \delta_0 + \sum_{m=1}^{8} \delta_m z_{mi} \qquad (6)$$

where, z_{mi} = variables representing socio-economic characteristics of the i^{th} household to explain inefficiency, *m*. The pure random disturbance, v_i, is detached from disturbances that can be attributed to the factors influencing efficiency, u_i, via δ_m ; m = 1, age (number of years of the farmer); *m* = 2, education (number of completed years of schooling of the farmer); *m* = 3, experience of growing rice (in years); *m* = 4, family size (total number of members of the household); *m* = 5, off-farm income share (includes the off-farm income as a % of total household income); *m* = 6, extension visits (no. of contacts); m = 7, access to microfinance (a dummy variable to capture the influence of microfinance on technical efficiency. Value is 1 if the farmer had obtained microfinance in the past 12 months prior to the survey, 0 otherwise); *m* = 8, Region (a dummy variable to capture the influence of geographic location on production efficiency. Value is 1 the farmer is located in the north-western region, 0 otherwise).

Model 2: Empirical model of the determinates of adoption of HYV rice

The empirical model of the effects of explanatory variables on the adoption of HYV Boro rice includes some farm and farmer's characteristics. The model also includes the farmer's perception which impacted on the adoption of HYV rice. We specified the following linear regression model by assuming that the adoption of HYV rice depended on the following explanatory variables

$$A = \omega_0 + \sum_{p=1}^{14} \omega_p z_{pi} \qquad (7)$$

where, A is the percentage of total rice area planted to HYV Boro rice; z_{pi} = variables represent farm and farmers' socio-economic characteristics in addition to farmers perception about the adoption of HYV Boro rice; ω_0 is the constant; p =1, age (number of years of the farmer); p = 2, education (the number of completed years of schooling of the farmer); p = 3, technical efficiency of farm household; p = 4, off-farm income share (includes the off-farm income as a % of total household income); p = 5, extension visits (no. of contacts); p = 6, access to microfinance (a dummy variable to capture the influence of microfinance on the adoption of HYV rice. Value is 1 the farmer obtained microfinance within the 12 months prior to the survey, 0 otherwise); p = 7, Region (dummy variable to capture the influence of geographic location on adoption. Value is 1 if the farmer is located in the north-western region, 0 otherwise); p = 8, (a dummy variable; 1 if the farmer is a member of a village local group, 0 otherwise); p = 9, price (a dummy variable; 1 = higher compared to TV, 0 = otherwise); p = 10, yield (a dummy variable; 1 = higher compared to TV, 0 = otherwise); p = 11, irrigation coverage (% of land holdings irrigated); p = 12, input costs per hectare of HYV Boro rice; p = 13, number of full-time agricultural workers in the family, p =14, farm size. Price and yield are used as farmer's perception of HYV Boro rice.

Data used for the estimation

Data were collected from 12 villages in north-west and north-central regions of Bangladesh by a survey conducted in June-August 2009. For microfinance borrowers, data were collected with the help of the client lists of Microfinance Institutions (MFIs). Personal interviews were conducted for both groups of borrowers and non-borrowers of microfinance. We interviewed 180 agricultural microfinance borrowers and also 180 non-borrowers as the control group. To avoid an 'endogenous confounding problem', we interviewed non-borrowers from those villages that had no microfinance program coverage. The samples of the microfinance borrowers were randomly selected without replacement from the borrower lists available from the local office of microfinance institutions in each microfinance village surveyed. Data were collected from the farmers producing Aus, Aman and Boro rice crops through multi-stage random sampling technique. Among these 360 farms, 354 holdings produced HYV Boro rice, 282 produced Aman and 92 produced Aus rice and were therefore taken as the final sample. It may be noted that the overall cropping intensity of the sampled regions was 157.75% which indicated that most farms grew two rice crops a year.

Description of the Data and Variables

Output was defined as the market value of rice production under Aus/Aman/Boro rice during the survey period. It was measured in Bangladesh Taka[2]. Rice output prices were gathered from individual farms. Land represented the total amount of land (own-cultivated land, sharecropping land, and rented/leased land) used for producing each rice crop and was measured in hectares. Labour comprised family (imputed as hired labour) and non-family hired labour for pre and post planting operations and harvesting excluding threshing and was measured in labour-days for each crop. Fertilisers include all sorts of organic and inorganic fertilisers used by the farm households for each rice crop. It represented the total cost of fertiliser and was measured in Taka. Seeds include all quantities of seeds used in each rice crop and was measured in Taka. If seedlings were purchased, that quantity was converted into the equivalent amount of seeds to compute the seed price. The irrigation comprised the irrigation costs for each rice crop. This cost was estimated from total rice land irrigated for each crop during the survey period. Tilling included the total land tilled by tractor and/or bullocks for each rice crop. It represented the total cost of tilling for each crop and was measured in Taka. Other costs included pesticide, seed bed preparation, and crop transportation costs and they were measured in Taka.

Some basic characteristics of the sample farms are presented in Table 1. It is evident that the farms were small in terms of their output and actual areas cropped. Farmers producing Boro rice obtained higher mean outputs per hectare of land cultivated compared to Aman and Aus rice crops. The per hectare yield variability was more pronounced for Boro rice [Coefficient of Variation (CV) = 0.9)] compared to Aus (CV = 0.84) and Aman (CV = 0.89) rice. Aman and Boro rice producers had mean education exceeding five years. Aman producers had the highest mean number of years of growing experience but had the lowest number of contacts with the extension officers. The table 1 shows that for inputs costs, Boro rice had highest expenditure in terms of all inputs, with fertilisers and irrigation being the major cost components.

Table 1. Summary of Inputs and Outputs

Variables	Units	Aus Mean (SD)	Aman Mean (SD)	Boro Mean (SD)
Output	Taka	22970.65 (19040.67)	40569.66 (47087.4)	51499.5 (66967.03)
Cultivated land	ha.	0.53 (0.52)	0.89 (1.15)	1.02 (1.39)
Labour	Man-days	59.38 (41.77)	87.06 (80.27)	117.60 (110.28)
Seeds	Taka	669.90 (708.13)	1243.56 (2259.65)	2235.99 (10602.56)
Fertilisers	Taka	3581.86 (4444.65)	3405.75 (5355.99)	9617.89 (18689.36)
Irrigation	Taka	1699.84 (2375.74)	768.56 (1972.44)	6379. 99 (10035.46)
Tilling Costs	Taka	1744.17 (2137.99)	2774.81 (3403.24)	3070.98 (4374.59)
Other expenditure	Taka	964.37 (942.35)	1233.88 (1518.75)	1972.44 (2882.98)
Age	Years	39.38 (12.26)	43.40 (12.71)	42.07 (12.58)
Education	Years	4.33 (4.34)	5.33 (4.84)	5.09 (4.75)
Experience	Years	20.66 (12.40)	24.23 (13.60)	23.01 (13.25)
Off-farm income share	%	38.31 (26.28)	33.88 (27.07)	35.38 (26.66)
Extension Visits	No.	6.02 (7.01)	5.89 (6.78)	6.05 (6.99)
Family size	No.	4.37 (1.89)	4.76 (1.83)	4.61 (1.80)

Note. SD, standard deviation

Empirical Results and Analysis

The maximum-likelihood estimates (MLE) of the parameters of the production function, given in equation (5), and the inefficiency model in equation (6) were estimated simultaneously using the computer program FRONTIER 4.1 (Coellli, 1996). The results are presented in Table 2. We can make some inferences about the data shown in Table 2. The constant terms for TVs (Aus and Aman) are higher than that obtained for HYV rice. It indicates that since TVs have been adopted over time with relatively low inputs and capital use, they give a higher basic yield compared to HYV. This finding conforms to that of Hayami and Ruttan (1985). The results also suggest that the responses of HYV rice with respect to fertilisers, irrigation, labour and other variable costs in particular are much more elastic for inputs than the inputs for TVs. The production elasticity estimates indicate that land contributed most to the production of the TVs and HYV rice and the estimates were 0.62, 0.73, and 0.64 *($p<0.01$)* for Aus, Aman and Boro rice respectively. Given that small areas of land were cultivated by the small farmers in Bangladesh, the high elasticity of land (which can be considered as a "quasi-fixed input") is not surprising for both HYV and TVs rice. These findings suggest that the enlargement of land would contribute significantly to increasing farm productivity. Regarding the average scale elasticities, producers of Aus and Aman crops operated marginally at decreasing returns to scale (0.9 and 0.87), whereas Boro producers substantially at increasing returns to scale (1.08). This finding is in line with those of Wadud and White (2000) and Coelli et al. (2002). For both the TV and HYV rice, the results are evenly distributed and suggest that the farms are neither too big nor too small and economies of scale may be realized only by the large farms, a finding similar to that of Coelli et al. (2002).

The estimated value of variance parameter $\gamma = \sigma_u^2 / (\sigma_u^2 + \sigma_v^2)$ is significant both for Aus and Boro rice crop at 1% level of significance which indicate that technical inefficiency have effects on the outputs of both Aus and Boro crops. This result is consistent with those reported by Coelli and Battese (1996), Wadud and White (2000), Sharma et al. (1999). The corresponding variance-ratio parameters[3], γ^*imply 52.15%, 5.2% and 6.5% of the differences between observed and frontier production for Aus, Aman and Boro rice respectively, was due to the existing differences among the farmers. The estimated value of σ_s^2 was also significant at the 1% level of significance for all rice crops and indicates that the conventional production function was not an adequate representation of the data. This result is line with those of Wadud and White (2000), Bozoglu and Ceyhan (2007).

Table 2. Maximum likelihood estimates of stochastic frontier for TVs and HYV rice

Variables	Parameters	TV Aus (N=92) Mean (t-ratios)	TV Aman (N =282) Mean (t-ratios)	HYV Boro (N =354) Mean (t-ratios)
Constant	β_0	5.22 (11.67)***	6.05 (22.10)***	4.39 (18.12)***
Ln (land)	β_1	0.62 (8.75)***	0.73 (14.51)***	0.64 (13.57)***
Ln (Labour)	β_2	0.02 (0.15)	-0.01 (-0.27)	0.13 (2.95)***
Ln (Seeds)	β_3	0.04 (0.80)	0.13 (3.02)***	0.06 (2.63)***
Ln (Fertilisers)	β_4	0.10 (2.17)**	-0.05 (-1.89)*	0.052 (1.69)*
Ln (Irrigation)	β_5	-0.002 (-0.18)	-0.002 (-0.32)	0.02 (1.46)
Ln (Tilling)	β_6	0.092 (1.43)	0.032 (0.78)	0.08 (2.58)***
Ln (Other expenditures)	β_7	0.026 (0.68)	0.04 (2.16)**	0.10 (3.59)***
Sum of elasticity of inputs		0.90	0.87	1.08
Variance parameters				
Sigma-squared	$\sigma_s^2 = \sigma_u^2 + \sigma_v^2$	0.28 (2.83)***	0.158 (5.68)***	0.16 (11.12)***
Gamma	$\gamma = \sigma_u^2 / (\sigma_u^2 + \sigma_v^2)$	0.75 (6.67)***	0.13 (0.58)	0.16 (1.75)*
Log-likelihood		-23.51	-122.93	-160.01
Inefficiency effects				
Constant	δ_0	2.43 (1.71)*	-0.72 (-2.10)**	-0.02 (-0.01)
Age	δ_1	0.05 (1.43)	0.01 (2.28)**	0.10 (1.78)*
Education	δ_2	-0.06 (-1.67)*	-0.002 (-0.14)	-0.02 (-1.95)*
Experience	δ_3	-0.04 (-1.27)	-0.01 (-2.18)**	-0.01 (2.70)***
Family size	δ_4	-0.08 (-0.85)	0.06 (1.14)	0.03 (1.36)
Off-farm income share	δ_5	0.093 (0.12)	1.29 (2.37)**	0.07 (0.52)
Extension visits	δ_6	-0.01 (0.78)	-0.01 (1.05)	-0.001 (-0.28)
Access to microfinance	δ_7	-1.23 (-2.19)**	-0.05 (-0.44)	-0.45 (-2.76)***
Region	δ_8	1.86 (1.97)**	0.19 (1.60)	0.296 (2.25)**

Note: *Significant at 10% level (P<0.10), **Significant at 5% level (P<0.05), ***Significant at 1% level (P<0.01). Figures in the parentheses are asymptotic t -ratios.

Results of hypotheses tests

A set of hypotheses on model selection and inefficiency specifications for Aus, Aman and Boro rice crops were tested using the Likelihood Ratio (LR) test statistic[4]. The null hypothesis that ($H_0 : \beta_8 ....\beta_{35} = 0$; here $\beta_8 ......\beta_{35}$ represents the quadratic terms and also the cross terms) the Cobb-Douglas function is an adequate representation of rice production was accepted at the 5% significance level for all rice crops in our study (LR statistics 1.16; 40.94 and 41.36< $\chi^2_{28,o.95}$ = 43.87). The second null hypothesis that ($\gamma = 0$) there is no technical inefficiency effects was rejected at the 5% significance level which implies that significant inefficiency effects exist and are indeed stochastic (LR statistics 23.64; 19.98 and 20.4 < $\chi^2_{1,o.95}$ = 2.71). This result is in line with previous empirical studies (Wadud and White, 2000; Minh and Long, 2009; Binam et al., 2004). The third null hypothesis that ($H_0 = \delta_0 = ...\delta_d = 0 \ \forall_d$) inefficiency effects are not present in the model, was also rejected at the 5% significance level for all rice crops (LR statistics 17.46; 19.84 and 20.38> $\lambda^2_{9,o.95}$ = 16.27). This indicates that the joint effects of these chosen variables on technical inefficiency are statistically significant. In summary, the results of the hypotheses indicate that the discrepancies between the observed production and frontier production for the three rice crops are due to the presence of technical inefficiencies.

Distribution of technical efficiency

The levels of technical efficiency of each farm surveyed for the three rice crops are presented in Table 4. We conducted a set of paired-difference *t-test* for each pair of the crops to test the null hypothesis that mean technical efficiency for each pair of crops, one pair at a time, were the same. These pair wise comparison supported the notion that mean technical efficiency of Aman rice is significantly higher for this sample (*t-ratio*: Aman versus Aus = 4.67; Aman versus Boro = 2.89). However, the average technical efficiency difference is lower in Aus than Boro (*t-ratio*: Aus versus Boro = *2.77*) rice. For testing the equality of means among the technical efficiency (TE) indices across the rice farming systems we conducted an ANOVA test (Table 3). We found no significant differences between the means of TE indices for three rice varieties (F statistic (1.62) < Critical value of $F_{2,\ 725}$ (3.11) and concluded that the TE indices are independent of the cultivation practices. We also used *Bartlett's Test* (Table 3) to test for the homogeneity of variances among the TE indices of the three rice crops following Binam et al. (2004). The null hypothesis that the variance is the same for all rice crops was overwhelmingly rejected at the 5% significant level (the Bartlett's Test Statistic 27.75 ($\lambda^2_{(2)}$)> Critical Chi-Square Value of 5.99 ($\lambda^2_{(2)}$) and we concluded that there were significant differences between the variances among the cropping systems.

Table3. ANOVA test of TE indices across Boro, Aman and Aus rice farming systems

Test	Distribution	Computed value	Critical value 5%	Null hypotheses H_0([a])
BARTLETT	$\chi^2_{(2)}$	27.75	5.99	Rejected
ANOVA	$F_{(2,\ 725)}$	1.62	3.11	Accepted

[a] $H_0 : \sigma_1^2 = \sigma_2^2 = \sigma_3^2$ *for Bartlett test;* $H_0 : TE_1 = TE_2 = TE_3$ *for ANOVA test*

The higher mean TE found for Aman rice production implies that farmers were higher up along their learning curves in its cultivation due to their extensive experience of rice growing Table (1). It may also be related to their greater flexibility in resource allocation at times of peak demand. The TE indices for the Aus rice variety ranged from 18% to 96% with an average of 86%. This suggests that if the average farmer in the Aus rice sample had achieved the TE level of his/her most efficient peer, then he/she would have realized an output gain of 10.08% (1 -[85.89/95.52]). Similarly, the most inefficient farm in this sample would have increased its output by as much as 81.15% (1 -[18.01/95.52]). The corresponding results for Aus rice show that there were significant variations in TE among the surveyed farms (Table 4). The coefficient of variation (= std. Dev/Mean) for Aus crop was 13.37% compared to 9.18% for the Aman crop and 10.29% for the Boro rice variety.

Table 4. Frequency distribution of efficiency measures for HYV and TV rice

Efficiency (%)	Aus		Aman		Boro	
	Number	% farms	Number	% farms	Number	% farms
≥ 0.90 ≤ 1.00	45	49	212	75.17	215	60.73
≥ 0.80 ≤ 0.90	34	37	39	13.83	86	24.29
≥ 0.70 ≤ 0.80	6	6.5	16	5.67	38	10.74
≥ 0.60 ≤ 0.70	3	3.25	9	3.19	12	3.39
≥ 0.50 ≤ 0.60	3	3.25	6	2.14	3	0.85
≥ 0.40 ≤ 0.50	0	0	0	0	0	0
≥ 0.30 ≤ 0.40	0	0	0	0	0	0
≥ 0.20 ≤ 0.30	0	0	0	0	0	0
≥ 0.10 ≤ 0.20	1	1	0	0	0	0
≥ 0 ≤ 0.10	0	0	0	0		
Mean		85.89		91.06		89.03
Std. Dev		11.48		8.36		9.16
Maximum		95.52		98.26		98.13
Minimum		18.01		51.58		57.58

The TE indices for Aman rice ranged from 52% to 98% with an average of 91%. This suggests that if the average farmer in the Aman rice sample had achieved the TE level of his/her most efficient peer, then he/she would have realized an output gain of 7.32% (1 -[91.06/98.26]). Similarly, the most inefficient farm in this sample could have increased its output by 47.51% (1 -[51.58/98.26]). The result shows that the Aman rice producers were producing at 91% of their potential production level given the existing state of technology, input levels and resource endowments. The TE indices for Boro rice ranged from 58% to 98% with an average of 89%. This implies that if the average farmers for the sample of Boro rice had achieved the TE level of his/her most efficient peer, then the that farmer would have realized an output gain of 9.07% (1 -[89.03/98.13]). Similarly, the most inefficient farmer in this sample would have increased the output by 41.32% (1 -[57.58/98.13]).

The mean TE values of 86%, 91%, and 89% obtained in this study are in line with those of the studies of Wadud (2000), Sharif and Dar (1996), Banik (1994), Dawson and Woodford (1991), Bozoglu and Ceyhan (2007).

Factors influencing farm technical inefficiency

The parameter estimates of the inefficiency model, estimated using equation (6), are listed in the lower part of Table 2. The results of the ML estimations show that age, education, experience, off-farm income share, access to microfinance and region had significant impacts on technical inefficiency (TI), whereas family size and extension contacts had only insignificant effects on the TI of farmers producing the three rice crops. Age had a significant positive impact on TI for Aman and Boro growers, which indicates that younger farmers were more efficient than their older counterparts in producing Aman and Boro crops. This result is consistent with previous studies (Bozoglu and Ceyhan, 2007; Coelli and Battese, 1996; Abdulai and Eberlin, 2001; Dolisca and Jolly, 2008). Older farmers are less receptive to using modern inputs, averse to have extension contacts and less willing to adopt new practices, a finding similar to that of Hussain (1989). The variable education was negatively related to all three rice crops and had significant negative impacts on the Aus and Boro crops. This finding supports the hypothesis of Schultz (1964) that education helps individuals to perceive, interpret and to respond to new innovations including the efficient use of inputs. This fact is particularly true for the Boro rice variety that is input intensive, especially so for chemical fertilisers, pesticides, and seeds. For Aman rice growers, education was not correlated with efficiency, a finding similar to those of Coelli et al. (2002). Experience was negatively associated with TIs of all rice crops as expected, and it was significantly negative for the TIs for both Aman and Boro rice crops. This finding suggests that experience of Aman and Broro rice farming leads to better managerial skills acquired over the years. This also indicates that optimum Aman and Boro rice production systems are highly dependent upon the experience of the farmers. Huffman (2001) also supported the views that farmers with more farming experience had greater technical efficiency.

The coefficient of the access to microfinance was negatively related to the TIs for all rice crops and it was significantly negative for Boro and Aus rice crops. This finding implies that access to microfinance reduces the TI of the sample farms. Access to microfinance also supports the *free cash-flow* hypothesis (Latruffe, 2004), which stipulates that access to credit has a positive influence on TE in that the indebted farmers face repayment obligations that encourage them to minimize waste and increase production. Credit thereby helps to mitigate financial constraints and to reduce inefficiencies (Binam et al., 2004). Credit also helps to increase farm revenue whereas a lack of credit decreases the efficiency of the farmers by limiting their adoption of high yielding varieties and in acquiring information for increased productivity (Wozniak 1993). Thus, improved access to agricultural microfinance remains an important factor for improving farm production efficiency in Bangladesh. The dummy variable *region* was positively related to the TIs for all rice crops. Thus farmers who produce rice in the north western region of Bangladesh perform less efficiently than those of the north central region. This finding reinforces the concept that crop specific regional focusing is a vital policy instrument that should be addressed in formulating agricultural policy in Bangladesh.

For Aus and Boro off-farm income share, family size, and extension visits were not significant variables. These findings indicate that farms with smaller family sizes and less off-farm income share tended to display higher TEs. Although not significant, the extension visits may be an important policy instrument by which the government could raise agricultural productivity as the agricultural extension visits enable the farmers to learn better farm management methods and more efficient uses of limited resources.

Factors influencing the adoption of HYV Boro rice

Farmers generally compare the characteristics of HYV with those of TVs before deciding whether to adopt HYV Boro rice. Other factors including production technology, resource endowments of farmers, institutional and market indicators may have profound bearings on the adoption of HYV Boro rice. Table 5 presents the results of the Tobit estimation of the determinants for adopting HYV Boro rice. The results show that all explanatory variables, with nine significant coefficients out of the 14 coefficients had the expected signs and indicate that the model was well fitted, as all the explanatory variables combined explain the adoption of HYV Boro rice. As expected, irrigation was found to be the most significant variable in determining the adoption of HYV Boro rice. The *t*-statistic of irrigation was the highest among the asymptotic values of the regression coefficients included in the model. This finding conforms to those of Hossain (1989) and Rahman (1986) who emphasized that the provision of irrigation had a positive influence on the adoption rate of HYV Boro rice. In terms of farm specific characteristics that significantly impacted on the adoption of HYV rice are farmers' age, education, technical efficiency, membership of village-local groups and the number of agricultural workers in the family.

We found a robust and significant positive effect of TE on the adoption of HYV rice. This supports our hypothesis that technical efficiency *per se* as an explanatory factor for adoption adds to our understanding of the HYV adoption process. It also suggests that there is considerable scope for enhancing the adoption of HYV rice through improving the technical efficiency of rice producers. The statistically significant coefficient age, as a proxy for farming experience, indicates that farmers that work in uncertain production environments are able to receive and evaluate information over their working lives and thereby influence their decision about adopting HYV Boro rice. Farmers in such environments continually experiment and adopt the HYV when they consider benefits of doing so are promising (Sall, et al., 2000). Off-farm income had a positive effect on the adoption of HYV Boro rice. This result conforms to those of Ransom et al. (2003). It might be explained by the fact that off-farm income share improves the experience and human capital of the rice producers since it is likely that farmers with large off-farm income shares may have family members who live outside of their respective villages. It helps not only to bring additional income that could be used for farm activities but also provides the opportunity to acquire novel farming information especially on new seeds varieties from other areas. The coefficient of the variable access to microfinance was statistically significant and showed the significant role of microfinance on the adoption of HYV Boro rice. With rising input prices, the provision of finance to small farmers still remains elusive in Bangladesh. Policies leading to providing loans to small farmers in ways that would ensure high rates of repayment with minimum interest costs are suggested. Consequently, streamlining the microfinance to the credit constrained farmers would be a vital factor in increasing the adoption of HYV Boro rice in Bangladesh. However, this is a multi-disciplinary problem that needs to be addressed more rigorously by the government policy makers in collaboration with Non Government Organizations (NGOs) and the donor agencies. The success and experience of the Grameen Bank, the pioneer of the microcredit concept, can be emulated on a sustainable basis in pursuing this goal.

Table 5. Factors affecting adoption of HYV Boro rice

Factors	Parameters	Coefficients	Marginal effects
Constant	ω_0	-1.1616*** (-2.58)	-0.4206
Age	ω_1	0.0033*(1.81)	0.0011
Education	ω_2	0.0096* (1.85)	0.0034
Technical efficiency	ω_3	1.2740*** (2.93)	0.4613
Off-farm income share	ω_4	0.0272(0.32)	0.0098
Extension visits	ω_5	0.0016(0.51)	0.0006
Access to microfinance	ω_6	0.2216**(2.12)	0.0044
Region	ω_7	0.1319**(2.21)	0.0477
Membership of local group	ω_8	0.082***(3.02)	0.059
Price	ω_9	-0.0868 (-1.24)	-0.00314
Yield	ω_{10}	0.0877***(2.97)	0.1130
Irrigation coverage (% of land holdings)	ω_{11}	1.0254***(9.69)	0.3713
Input cost per hectare	ω_{12}	-0.1129***(-1.76)	-0.0004
Number of Agricultural workers	ω_{13}	0.0153*(1.65)	0.0141
Farm size	ω_{14}	-0.00004 (-0.72)	-0.00001

*Note: *Significant at 10% level (P<0.10), **Significant at 5% level (P<0.05), ***Significant at 1% level (P<0.01). Figures in the parentheses are asymptotic t- ratios.*

The results also show that larger families with more agricultural workers are conducive to the adoption of HYV Boro rice. Larger families with more agricultural workers may facilitate the timely availability of labour and gain knowledge of the technical know-how required for HYV Boro rice production. Hollaway et al. (2002) also reported similar results indicating that higher subsistence pressure can lead to increasing the adoption of new agricultural technologies that ensure continuous food access for these households. The coefficient of the member of a local group was positive and statistically significant. It implies that members of a local group are more informed about better techniques of production through group interactions and are able to access more easily the potential impacts of new technology on their farming operations. This finding conforms to that of Gregersen et al. (1989). On the other hand, non-members may not be informed about technological innovation, which may lead them to overestimate the costs and undervalue the potential benefits. Thus it is evident that the communication network of farmers may have a profound influence on the decision to adopt HYV Boro rice. It may also give farmers more opportunity to be exposed to adopting the improved varieties.

The significant higher input costs of Boro rice production, as a perception variable, supports the common notion of the high production costs as the reason for not adopting the HYV Boro rice by some farmers. Therefore, greater emphasis of timely availability of fertilisers, seeds, irrigation and pesticides at reasonable prices should be encouraged. The coefficient of the area of the land was negative, which supports the hypothesis that small farmers are faster at adopting HYV when the potential gains are demonstrable (Allauddin and Tisdell 1988; Hollaway et al., 2002) and that small farmers quickly adopt new innovations at a faster rate than those of large farmers. The statistically significant coefficient of yield, as a perception variable, implies that HYV Boro rice when compared favorably to TVs, would be adopted by the farmers. However, the other perception variable, price was negative, which implied that when HYV Boro rice was compared unfavorably to TVs, this would have a negative impact on its adoption. Policies that lead to ensuring higher prices for HYV Boro rice by all tiers of government would have a positive impact on the adoption of HYV Boro rice. The marginal effects of the censored regression model are simply the probability of the outcomes multiplied by the estimated coefficients, which evaluate the effects of each independent variable on the adoption of HYV rice. For instance, the marginal effect of 0.4613 for TE implies that for all respondents, every 1% increase in TE would increase the adoption of HYV Boro rice by 0.46%. Similarly, every 1% increase in irrigation coverage would increase the adoption of HYV rice by 0.37%.

Conclusions

This paper used stochastic frontier production functions to analyze the technical efficiency of TVs and HYV rice farmers in relation to their adoption of HYV rice growing in Bangladesh. It used detailed survey data obtained from 360 rice farms of 12 villages in 2008/2009 growing seasons. The mean technical efficiency of Aus and Aman rice crops were 86% and 92% respectively whereas for Boro (HYV) rice the technical efficiency was 89% which suggested substantial gains in output with given technology and resource endowments. It is evident that the farmers are tightly distributed at the upper end of the technical efficiency distribution for both TV and HYV rice. However, HYV rice producers had greater variability in per hectare yields and technical efficiency distribution. The empirical results revealed that inefficiency exists in the TVs and HYV rice production systems. Factors such as education, experience, extension visits and access to microfinance negatively influenced technical inefficiency, whereas age, family size, off-farm income and regional dummy showed a positive relation with technical inefficiency.

The study also assessed and identified factors that influence the adoption of HYV Boro rice using the Tobit model. The factors which influenced the adoption of HYV rice included farmers' age and education, technical efficiency, irrigation coverage, off-farm income, access to microfinance, perception of yield, membership of village-level organizations and cost of production per hectare. The significant positive impact of technical efficiency on the adoption rate of HYV rice shows that farmers with higher technical efficiency were able to transform their production systems to more efficient methods by adopting new technologies, changing production functions, intensively seeking improved farming practices from extension officers, research staff and other accessible private farm advisers. From a policy perspective, more concerted efforts directed at increasing the technical efficiency of HYV rice farms are likely to increase the adoption rate of HYV rice in Bangladesh. The results of the inefficiency model and factors that influence the adoption of HYV rice indicate that some common factors such as age, education, experience, access to microfinance, off-farm income, and region have significant impacts on technical inefficiency and on the decision to adopt HYV Boro rice. An insight into the above factors has clear implications as to how the technical inefficiency of both the TVs and HYV rice may be reduced and the adoption rate of HYV Boro rice may also be improved at a faster rate.

Thus policies leading to raising the educational level of the farmer, increasing their technical efficiency, ensuring greater access to microfinance, crop specific regional focusing and strengthening the extension services through more intensive on-farm demonstrations could be beneficial to increasing technical efficiency and adoption of HYV rice in Bangladesh.

Notes

[1] Feder et al. (1985) has defined *'adoption'* as the percentage of farmers who have adopted a new technology or the area under a new technology. The *'intensity'* of adoption is defined as the level of adoption of a given technology.

[2] USD 1= Taka 69.45, Euro 1=Taka 86.75 (as of July 15, 2010).

[3] The relative contribution of the variance of inefficiency effect to the total variance (γ^*) is equal to $\gamma^* = \gamma / [\gamma + (1-\gamma)\pi/(\pi-2)]$ (Coelli et al., 1998; Binam et al., 2004; Rahman, 2003).

[4] The likelihood-ratio test statistic, $\lambda = -2\{\ln[\text{likelihood } (H_0) - \ln[\text{likelihood}(H_1)]\}$, has approximately λ_v^2 distribution with v equal to the number of parameters assumed to be zero in the null hypothesis, (H_0), provided. The critical value of the χ^2 is taken form Kodde and Palm (1986, Table 1).

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