PROFIT EFFICIENCY AMONG BANGLADESHI RICE FARMERS

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ABSTRACT

Production inefficiency is usually analysed by its two components – technical efficiency and allocative efficiency. In this study we provide a direct measure of production efficiency of the Bangladeshi rice farmers using a stochastic profit frontier and inefficiency effects model. The data, which is for 1996, includes seven conventional inputs and several other background factors affecting production of modern or high yielding varieties (HYVs) of rice spread across 21 villages in three agro-ecological regions of Bangladesh. The results show that there are high levels of inefficiency in modern rice cultivation. The mean level of profit efficiency is 77% suggesting that an estimated 23% of the profit is lost due to a combination of both technical and allocative inefficiency in modern rice production. The efficiency differences are explained largely by infrastructure, soil fertility, experience, extension services, tenancy and share of non-agricultural income.

JEL Classification: O33, Q18, and C21
Keywords: Stochastic profit frontier, profit efficiency, Bangladesh

INTRODUCTION

Bangladesh agriculture, dominated by rice production, is already operating at its land frontier and has very little or no scope to increase the supply of land to meet the growing demand for food required for its ever-increasing population. The expansion in crop area, which was a major source of production growth till the 1980s, has been exhausted and the area under rice started to decline thereafter (Husain et al., 2001). The observed growth in rice production, at an annual rate of 2.34% for the period 1973 – 1999, has been largely attributed to conversion of traditional rice to modern varieties rather than to increases in yields of modern rice varieties (Baffes and Gautam, 2001). Furthermore, the conversion potential from local to modern varieties seems to be limited as the ceiling adoption level of modern varieties in Bangladesh appears to be reached (Bera and Kelly, 1990). Currently, 61% of total rice area is allocated to modern varieties and the upper bound of conversion, set at 85% by Baffes and Gautam (2001), already seems to be optimistic as it assumes a minor increase in gross rice area while past experience revealed a stagnancy and/or minor decline in land under rice. Therefore, the principal solution to increasing food production lies in raising the productivity of land by closing the existing yield gaps and developing varieties with higher yield potential. On the other end of the spectrum, the United Nations projects that farmers will have to generate large marketable surplus to feed the growing urban population (estimated at 46% of total population of 173 million) by 2020 (Husain et al., 2001). This implies that Bangladeshi farmers not only need to be more efficient in their production activities, but also to be responsive to market indicators, so that the scarce resources are utilized efficiently to increase productivity as well as profitability, and ensure supply to the urban market. Furthermore, efficiency gains will have a positive impact on raising farm income of these largely resource poor farmers. In fact, real income from modern rice farming over the past decade has fallen by 18% owing to stagnant output price and rising costs of production coupled with declining productivity.

Given this backdrop, the present study sets out to analyse profit efficiency of the modern rice farmers and to identify farm-specific characteristics that explain variation in efficiency of individual farmers. The relationships between efficiency, market indicators and household characteristics have not been well studied in Bangladesh.

An understanding of these relationships could provide the policymakers with information to design programmes that can contribute to measures needed to expand the food production potential of the nation. Few past studies were available on measuring efficiency among Bangladeshi rice farmers and have been narrow in their focus either in terms of data coverage or in the use of functional form for econometric analyses and concentrated mainly on measuring technical efficiency only (Wadud and White, 2000; Sharif and Dar, 1996; and Deb, 1995). Earlier, Hossain (1989) covered allocative efficiency using nationally representative survey of 16 villages but his data dates back to 1982. Only recently, Coelli et al., (2002) computed technical, allocative, cost and scale efficiencies using non-parametric approach. Technical efficiency estimates for modern rice cultivation from these studies range between 74 – 82% implying that considerable scope exists in improving technical efficiency component alone. Allocative efficiency, on the other hand, is estimated at 81% for modern rice in Bangladesh (Coelli, et al., 2002).

The paper proceeds as follows. The next section outlines the concept of profit efficiency and the use of a stochastic profit frontier, and the inefficiency effects model for its measurement. Section three describes the data. The fourth reports and interprets the results and tests for the significance of the policy-relevant inefficiency variables and the fifth section concludes.

MEASURING EFFICIENCY USING FRONTIER PROFIT FUNCTION

Production inefficiency is usually analysed by its two components – technical and allocative efficiency. In a production context, technical efficiency relates to the degree to which a farmer produces the maximum feasible output from a given bundle of inputs (an output oriented measure), or uses the minimum feasible level of inputs to produce a given level of output (an input oriented measure). Allocative efficiency, on the other hand, relates to the degree to which a farmer utilizes inputs in optimal proportions, given the observed input prices (for details, see Coelli et al., 2002). Recent developments combine both measures into one system, which enables more efficient estimates to be obtained by simultaneous estimation of the system (e.g., Ali and Flinn, 1989; and Wang, et al., 1996). The popular approach to measure efficiency, the technical efficiency component, is the use of frontier production function[1] (e.g., Tzouvelekas et al., 2001; Wadud and White, 2000; Sharma et al., 1999; Sharif and Dar, 1996; Battesse and Coelli, 1995, Battesse, 1992; Russell and Young, 1983). However, Yotopolous and others argue that a production function approach to measure efficiency may not be appropriate when farmers face different prices and have different factor endowments (Ali and Flinn, 1989). This led to the application of stochastic profit function models to estimate farm specific efficiency directly[2] (e.g., Ali and Flinn, 1989; Kumbhakar and Bhattacharya, 1992; Ali et al., 1994; and Wang et al., 1996).

The profit function approach combines the concepts of technical and allocative efficiency in the profit relationship and any errors in the production decision are assumed to be translated into lower profits or revenue for the producer (Ali et al., 1994). Profit efficiency, therefore, is defined as the ability of a farm to achieve highest possible profit given the prices and levels of fixed factors of that farm and profit inefficiency in this context is defined as loss of profit from not operating on the frontier (Ali and Flinn, 1989).

Also, in a number of studies on efficiency measurement (e.g., Sharif and Dar, 1996; Wang et al., 1996), the predicted efficiency indices were regressed against a number of household characteristics, in an attempt to explain the observed differences in efficiency among farms, using a two-stage procedure.

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[1] The measurement of firm level efficiency has become commonplace with the development of frontier production functions. The approach can be deterministic, where all deviations from the frontier are attributed to inefficiency, or stochastic, which is a considerable improvement, since it is possible to discriminate between random errors and differences in inefficiency.

[2] In contrast with the widespread use of frontier production functions to estimate efficiency, use of profit frontier approach is highly limited.

Although this exercise has been recognized as a useful one, the two-stage estimation procedure utilized for this exercise has also been recognised as one which is inconsistent in its assumptions regarding the independence of the inefficiency effects in the two estimation stages[3]

(Coelli, 1996). Battesse and Coelli (1995) extended the stochastic production frontier model by suggesting that the inefficiency effects can be expressed as a linear function of explanatory variables, reflecting farm-specific characteristics. The advantage of Battesse and Coelli (1995) model is that it allows estimation of the farm specific efficiency scores and the factors explaining efficiency differentials among farmers in a single stage estimation procedure. The present paper utilises this Battesse and Coelli (1995) model by postulating a profit function, which is assumed to behave in a manner consistent with the stochastic frontier concept. This model is applied to a large sample of rice producers in three agro-ecological regions of Bangladesh, differentiated by variety and by season.

The stochastic profit function is defined as

$$\pi_i = f(P_{ij}, Z_{ik}).\ exp\ (\xi_i) \tag{1}$$

where π_i is normalized profit of the ith farm defined as gross revenue less variable cost, divided by farm-specific output price; P_{ij} is the price of jth variable input faced by the ith farm divided by output price; Z_{ik} is level of the kth fixed factor on the ith farm; ξ_i is an error term; and $i = 1$, ….., n, is the number of farms in the sample.

The error term ξ_i is assumed to behave in a manner consistent with the frontier concept (Ali and Flinn, 1989), i.e.,

$$\xi_i = v_i - u_I \tag{1a}$$

where v_is are assumed to be independently and identically distributed $N(0,\sigma^2_v)$ two sided random errors, independent of the u_is; and the u_is are non-negative random variables, associated with inefficiency in production, which are assumed to be independently distributed as truncations at zero of the normal distribution with mean, $\mu_i = \delta_0 + \sum_d \delta_d W_{di}$ and variance σ_u^2 $(|N(\mu,, \sigma^2_u|)$, where W_{di} is the dth explanatory variable associated with inefficiencies on farm i and δ_0 and δ_d are the unknown parameters.

The production/profit efficiency of farm i in the context of the stochastic frontier profit function is defined as

$$EFF_i = E[\exp(-u_i) \mid \xi_i] = E[\exp(-\delta_0 - \sum_{d=1}^{D} \delta_d W_{di}) \mid \xi_i] \tag{2}$$

where E is the expectation operator. This is achieved by obtaining the expressions for the conditional expectation u_i upon the observed value of ξ_i. The method of maximum likelihood is used to estimate the unknown parameters, with the stochastic frontier and the inefficiency effects functions estimated simultaneously. The likelihood function is expressed in term of the variance parameters, $\sigma^2 = \sigma_v^2 + \sigma_u^2$ and $\gamma = \sigma_u^2 / \sigma^2$ (Battesse and Coelli, 1995).

DATA AND THE EMPIRICAL MODEL

Data

Primary data for the study pertains to an intensive farm-survey of rice producers conducted during February to April 1997 in three agro-ecological regions of Bangladesh. Samples were collected from eight villages of the Jamalpur Sadar sub-district of Jamalpur, representing wet agro-ecology, six villages of the Manirampur sub-district of Jessore, representing dry agro-ecology, and seven villages of the Matlab sub-district of Chandpur, representing wet agro-ecology in an agriculturally advanced area. A total of 406 farm households from these 21 villages were selected following a multistage stratified random sampling procedure.

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[3] In this commonly used two-stage approach, the first stage involves the specification and estimation of the stochastic frontier function and the prediction of inefficiency effects, under the assumption that these inefficiency effects are identically distributed with one-sided error terms. The second stage involves the specification of a regression model for predicted inefficiency effects, which contradicts the assumption of an identically distributed one-sided error term in the stochastic frontier (Kumbhakar et al., 1991; Battesse and Coelli, 1995).

Among these 406 farms, 380 farms produced modern varieties of rice and therefore taken as the final sample size.

In analysing crop production, it is often the case that data is only available for the major inputs, such as land, labour, fertiliser, and animal power. However, crop production is affected by many other variables that play significant roles in explaining performance. In this study, an attempt was made to collect information on most of the inputs used for rice production. Thus, information on the use of seeds, pesticides, and farm capital assets was collected. This is expected to increase the explanatory power of the analyses significantly. It is often argued that seeds and animal power services are more or less used in fixed proportions, so their omission is not important (Hossain, 1989 and Hossain et al., 1990), but results here suggest that this is not the case.

Empirical Model

The general form of the translog profit frontier, dropping the *i*th subscript for the farm, is defined as:

$$\ln \pi' = \alpha_0 + \sum_{j=1}^{5} \alpha_j \ln P'_j + \tfrac{1}{2} \sum_{j=1}^{5} \sum_{k=1}^{5} \tau_{jk} \ln P'_j \ln P'_k + \sum_{j=1}^{5} \sum_{l=1}^{2} \phi_{jl} \ln P'_j \ln Z_l$$

$$+ \sum_{l=1}^{m} \beta_l \ln Z_l + \tfrac{1}{2} \sum_{l=1}^{2} \sum_{t=1}^{2} \varphi_{lt} \ln Z_l \ln Z_t + v - u \qquad (3a)$$

and

$$u = \delta_0 + \sum_{d=1}^{7} \delta_d W_d + \omega \qquad (3b)$$

where

π' = restricted profit (total revenue less total cost of variable inputs) normalised by price of output (P_y),
P'_j = price of the *j*th input (P_j) normalized by the output price (P_y),
j = 1, fertilizer price
= 2, labour wage
= 3, animal power price
= 4, seed price
= 5, pesticide price
Z_l = quantity of fixed input, l
l = 1, area under modern rice varieties
= 2, farm capital used
v = two sided random error
u = one sided half-normal error
ln = natural logarithm
W_d = variables representing socio-economic characteristics of the farm to explain inefficiency, d
d = 1, tenancy (proportion of rented-in land cultivated by the farmer)
= 2, education (number of completed year of schooling)
= 3, experience in actually growing modern varieties of rice (number of years)
= 4, extension contact (dummy variable to measure the influence of agricultural extension on efficiency. Value is 1 if the farmer has had contact with an Agricultural Extension Officer in the past year, 0 otherwise)
= 5, index of underdevelopment of infrastructure[4]
= 6, index of soil fertility[5]

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[4] A composite index of underdevelopment of infrastructure was constructed using the cost of access approach. A total of 13 elements are considered for its construction. These are, primary market, secondary market, storage facility, rice mill, paved road, bus stop, bank, union office, agricultural extension office, high school, college, thana (sub-district) headquarter, and post office. Note that a high index value indicates a highly underdeveloped infrastructure (see Ahmed and Hossain, 1990 for construction details).

[5] The soil fertility index is constructed from test results of soil samples collected from the study villages during the field survey. Ten soil fertility parameters were tested. These are: soil pH, available nitrogen, available potassium, available phosphorus, available sulphur, available zinc, soil texture, soil organic matter content, cation exchange capacity (CEC) of soil, and electrical conductivity of soil. A high index value refers to better soil fertility.

= 7, non-agricultural income share (proportion of total household income obtained from non-agricultural sources)

ω = two sided random error

$\alpha_0, \alpha_j, \tau_{jk}, \beta_l, \phi_{jl}, \varphi_{lt}, \delta_0,$ and δ_d are the parameters to be estimated.

RESULTS

The summary statistics of the variables used appears in Table 1. A number of points can be noted from Table 1. First, we note that these farms are small, with average sizes of only three-quarter of a hectare. The average level of education of the farmers is less than four years; the average duration of actually growing modern rice varieties is 10 years; 19% of income is derived from off-farm; approximately 30% of total cultivated land per farm is rented-in; and only 11% of farmers have had contact with extension officers during the past year.

Table 1. Summary statistics.

Variables	Mean	Standard deviation
Output, profits and prices		
Rice output (kg)	2974.51	3153.39
Profit (taka[a])	10,203.70	12,345.30
Rice price (taka/kg)	5.64	0.44
Fertilizer price (taka/kg)	6.42	1.14
Labour wage (taka/day)	45.48	8.26
Animal power (taka/pair-day)	84.63	17.77
Seed price (taka/kg)	9.90	1.09
Pesticide price (taka/100 gm or ml)	83.58	15.56
Land cultivated (ha)	0.73	0.79
Farm capital (taka)	4,366.57	13,306.50
Farm-specific variables		
Tenancy (%)	30.23	39.36
Education of the farmer (years)	3.65	4.27
Experience (years)	10.31	5.34
Extension contact (%)	10.53	30.73
Infrastructure index (number)	34.25	14.88
Soil fertility index (number)	1.69	0.19
Non-agricultural income share (%)	18.64	28.84
Number of observations	380	

Note: [a] Exchange rate: 1 US dollar = 42.7 Taka (approximately) during 1996-97 (BBS, 2001).

The structure of modern rice production

The maximum-likelihood estimates (MLE) of the parameters of translog stochastic frontier profit function[6] defined by equation (3a), given the specifications for the inefficiency effects defined by (3b), were obtained using FRONTIER 4.1 (Coelli, 1996). The results of the profit frontier function are presented in the upper part of Table 2.

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[6] Among the regularity properties of the profit function specified in equation (3a), homogeneity was automatically imposed because the normalized specification was used. The monotonicity property of a translog profit function model holds if the estimated output share is positive (Wall and Fisher, 1987 cited in Farooq et al., 2001). To test this property we have estimated the deterministic version of the normalized profit function model complete with five variable input share equations using Zellner's SURE procedure (see Appendix for details). Result of this exercise confirmed that the monotonicity property holds. The symmetry property was tested by imposing cross-equation restrictions of equality on the corresponding parameters between the deterministic profit function and five variable input share equations. The test failed to reject the restrictions, thereby confirming that the symmetry property also holds. The convexity property is assumed to hold and, therefore, not tested.

Table 2. Maximum likelihood estimates of profit frontier functions.

Variables	**Parameters**	**Coefficients**	**t-ratio**
Profit function			
Constant	α_0	18.0156	14.71 ***
lnP'_F	α_F	2.5399	2.37 **
lnP'_W	α_W	-2.3267	-2.09 **
lnP'_M	α_M	-1.9973	-2.16 **
lnP'_S	α_S	-2.1921	-1.96 **
lnP'_P	α_P	-2.9356	-2.79 ***
$½lnP'_F$ x lnP'_F	τ_{FF}	0.4655	0.48
$½lnP'_W$ x lnP'_W	τ_{WW}	-0.0021	0.00
$½lnP'_M$ x lnP'_M	τ_{MM}	-0.5563	-0.81
$½lnP'_S$ x lnP'_S	τ_{SS}	-1.0734	-0.98
$½lnP'_P$ x lnP'_P	τ_{PP}	-0.4158	-1.26
lnP'_F x lnP'_W	τ_{FW}	0.0604	0.09
lnP'_F x lnP'_M	τ_{FM}	-0.8533	-1.60
lnP'_F x lnP'_S	τ_{FS}	0.0387	0.04
lnP'_F x lnP'_P	τ_{FP}	-0.2840	-0.52
lnP'_W x lnP'_M	τ_{WM}	0.1617	0.27
lnP'_W x lnP'_S	τ_{WS}	1.0942	1.16
lnP'_W x lnP'_P	τ_{WP}	0.6789	1.22
lnP'_M x lnP'_S	τ_{MS}	0.5887	0.79
lnP'_M x lnP'_P	τ_{MP}	0.9615	2.22 **
lnP'_S x lnP'_P	τ_{SP}	-0.8661	-1.15
lnP'_F x lnZ_L	ϕ_{FL}	0.0535	0.42
lnP'_F x lnZ_A	ϕ_{FA}	0.0023	0.03
lnP'_W x lnZ_L	ϕ_{WL}	0.1336	0.84
lnP'_W x lnZ_A	ϕ_{WA}	-0.0483	-0.55
lnP'_M x lnZ_L	ϕ_{ML}	-0.0421	-0.40
lnP'_M x lnZ_A	ϕ_{MA}	0.0347	0.46
lnP'_S x lnZ_L	ϕ_{SL}	-0.4251	-2.24 **
lnP'_S x lnZ_A	ϕ_{SA}	0.1107	1.07
lnP'_P x lnZ_L	ϕ_{PL}	-0.1370	-1.36
lnP'_P x lnZ_A	ϕ_{PA}	0.0258	0.36
lnZ_L	β_L	1.3032	3.40 ***
lnZ_A	β_A	-0.0107	-0.04
$½lnZ_L$ x lnZ_L	φ_{LL}	-0.0827	-1.96 *
$½lnZ_A$ x lnZ_A	φ_{AA}	-0.0094	-0.57
lnZ_l x lnZ_A	φ_{LA}	0.0051	0.24
Variance Parameters			
$\sigma^2 = \sigma_u^2 + \sigma_v^2$	σ^2	0.6512	2.64 ***
$\gamma = \sigma_u^2/(\sigma_u^2 + \sigma_v^2)$	γ	0.8644	15.14 ***
Log likelihood		-184.46	
Inefficiency effects			
Constant	δ_0	2.2028	1.79 *
Tenancy	δ_1	0.4168	1.71 *
Education	δ_2	0.0120	0.64
Experience growing MV	δ_3	-0.0470	-1.74 *
Extension	δ_4	-2.9783	-1.52
Infrastructure	δ_5	0.0240	2.62 ***
Soil fertility	δ_6	-2.5654	-1.88 *
Non-farm income	δ_7	1.0701	2.24 **
Number of observations		380	

Note: *** significant at 1 percent level ($p<0.01$)
** significant at 5 percent level ($p<0.05$)
* significant at 10 percent level ($p<0.10$)

F = fertilizer, W = labour, M = animal power, S = seed, P = pesticide, L = land, A = stock of farm capital asset.

The lower section of Table 2 reports the results of testing the hypothesis that the efficiency effects jointly estimated with the profit frontier function are not simply random errors. The key parameter is $\gamma = \sigma_u^2/(\sigma_u^2 + \sigma_v^2)$, which is the ratio of the errors in equation (1) and is bounded between zero and one, where if $\gamma = 0$, inefficiency is not present, and if $\gamma = 1$, there is no random noise[7]. The estimated value of γ is close to 1 and is significantly different from zero, thereby, establishing the fact that a high level of inefficiencies exists in modern rice farming. Moreover, the corresponding variance-ratio parameter[8] γ^* implies that 69.8% of the differences between observed and the maximum frontier profits for modern rice farming is due to the existing differences in efficiency levels among farmers.

Further, a set of hypothesis on different inefficiency specifications using Likelihood Ratio (LR) test statistic[9] was tested. The null hypothesis that $\gamma = 0$ is rejected at the 5% level of significance confirming that inefficiencies exist and are indeed stochastic (LR statistic $17.89 > \chi^2_{1,0.95} = 3.84$). In addition, the null hypothesis that $\gamma = \delta_0 = \delta_d = 0\ \forall_d$, which means that the inefficiency effects are not present in the model, is also rejected at the 5% level of significance (LR statistic $51.92 > \chi^2_{8,0.95} = 14.85$). Thus, a significant part of the variability in profits among farms is explained by the existing differences in the level of technical and allocative inefficiencies.

Based on the joint parameter estimates of the deterministic profit function along with five variable input share equations (see Appendix: Table A1), we computed basic features of the production structure, namely, the input and output shares and profit elasticities with respect to changes in variable input prices and fixed factors, shown in Tables 3 and 4, respectively. The difference between estimated and actual input shares is negligible (statistically insignificant), thereby rendering confidence in the results (Table 3). Cost of labour dominates the profit share followed by animal power services. Chemicals (fertilizers and pesticides) also account for 20% of profit share. Profitability increases sharply with increase in output (rice) price (Table 4). The profit elasticity with respect to output price is estimated at 1.92 indicating that a 1% increase in price of rice will increase profits by almost 2%. On the other hand, 1% rise in labour wage will reduce profitability by 0.42% followed by animal power services (0.20%) and fertilizers (0.15%), respectively. Profit response to land under cultivation is also very high as expected. The elasticity estimate reveals that a 1% increase in area under cultivation will raise profits by almost 1%. The incremental contribution of farm capital to profit is very poor although positive.

Table 3. The shares of variable inputs and output in modern rice production.

Type of shares	**Actual share**		**Estimated share[a]**	
	Mean	**Standard deviation**	**Mean**	**Standard deviation**
Variable input shares				
Fertilizer	0.1586	0.1321	0.1543	0.0512
Labour	0.4456	0.3565	0.4295	0.1093
Animal power	0.2061	0.1441	0.1995	0.0295
Seed	0.0923	0.0699	0.0899	0.0247
Pesticides	0.0488	0.0783	0.0470	0.0284
Output share	1.9539	0.6932	1.9201	0.1974

Note: Estimates are based on the results of the full system of deterministic profit function estimated jointly with five variable input share equations (see Appendix Table A1 for details).

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[7] If γ is not significantly different from zero, the variance of the inefficiency effects (ω in equation 3b) is zero and the model reduces to a mean response function in which the inefficiency variables enter directly (Battese and Coelli, 1995).

[8] The parameter γ is not equal to the ratio of the variance of the efficiency effects to the total residual variance because the variance of u_i is equal to $[(\pi-2)/\pi]\sigma^2$ not σ^2. The relative contribution of the inefficiency effect to the total variance term (γ^*) is equal to $\gamma^* = \gamma/[\gamma+(1-\gamma)\pi/(\pi-2)]$ (Coelli et al., 1998).

[9] The likelihood-ratio test statistic, $\lambda = -2\{\log[\text{Likelihood }(H_0)] - \log[\text{Likelihood }(H_1)]\}$ has approximately χ^2_ν distribution with ν equal to the number of parameters assumed to be zero in the null hypothesis. To conduct the tests involving γ parameter, the critical value of the χ^2 is taken from Kodde and Palm (1986, Table 1).

Table 4. Estimated profit elasticities.

Prices and fixed inputs	**Profit elasticity**
With respect to:	
Paddy price	1.9201
Fertilizer price	-0.1543
Labour wage	-0.4295
Animal power price	-0.1995
Seed price	-0.0899
Pesticide price	-0.0470
Land	0.9672
Capital	0.0478

Note: Estimates are based on the results of the full system of deterministic profit function estimated jointly with five variable input share equations (see Appendix Table A1 for details).

Production/profit Efficiency

The distribution of profit efficiency of modern rice farming is presented in Figure 1. The average profit efficiency score is 0.77 implying that the average farm producing modern rice could increase profits by 23% by improving their technical and allocative efficiency. Farmers exhibit a wide range of profit inefficiency in both seasons, ranging from 83.2% less than maximum profit to 5.9% less than maximum profit. Observation of wide variation in profit efficiency is not surprising and similar to the results from Pakistan and China. For example, Ali and Flinn (1989) reported mean profit efficiency level of 0.69 (range 13 to 95%) for Basmati rice producers of Pakistan Punjab. Ali et al., (1994) reported mean profit efficiency level of 0.75 (range 4 to 90%) for rice producers in North-West Frontier province of Pakistan. Wang et al., (1996) reported mean profit efficiency level of 0.62 (range 6 to 93%) for rural farm households in China. Despite wide variation in efficiency, about 55% of modern rice farmers seem to be skewed towards profit efficiency level of 80% and above (Figure 1). Nevertheless, the results imply that a considerable amount of profit can be obtained by improving technical and allocative efficiency in Bangladeshi rice production.

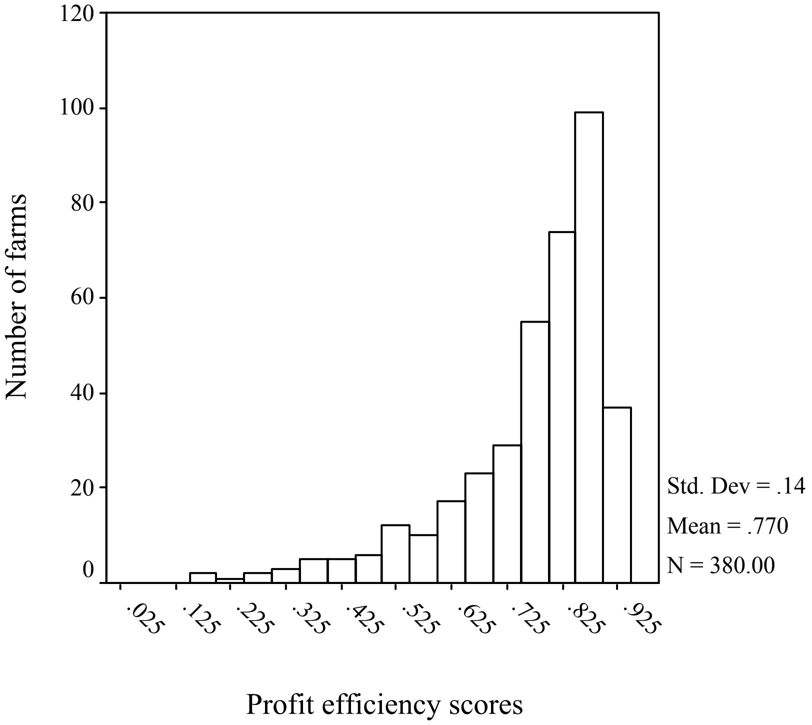

Figure 1. Profit efficiency of modern rice farmers.

Estimation of profit-loss[10] given prices and fixed factor endowments reveals that modern rice farmers are losing to the tune of Tk. 3544.4 per ha which could be recovered by eliminating technical and allocative efficiency (Table 5).

Table 5. Profit-loss in modern rice farming and key constraints.

Farm-specific characteristics	**N**	**Actual profit per ha**	**Estimated profit-loss[a] per ha**	**Profit efficiency**
Profit loss by tenurial status				
Owner operators (no rented-in lands)	219	13756.08	3309.57	0.78
Tenants	161	14182.33	3863.87	0.76
t-ratio (Owner vs. tenants)		-0.60	-3.23***	1.66*
Profit loss by education level				
Some education	190	13913.09	3235.32	0.78
Zero education	190	13960.27	3853.52	0.76
t-ratio (Education vs. no education)		-0.07	-3.66***	1.89*
Profit loss by experience in growing modern rice				
More than three years of experience	353	14127.40	3505.37	0.77
Up to three years of experience	27	11443.11	4054.95	0.70
t-ratio (More vs. less experienced)		1.99**	-1.65*	2.50***
Profit loss by extension services				
Farmers having extension contacts	40	15878.04	1659.73	0.90
Farmers not having extension contacts	340	13708.28	3766.15	0.75
t-ratio (Extension vs. no extension)		2.11**	-8.15***	6.21***
Profit loss by level of infrastructure[b]				
Developed infrastructure	195	14700.60	3212.24	0.80
Underdeveloped infrastructure	185	13131.45	3894.55	0.74
t-ratio (Developed vs. underdeveloped)		2.26**	-4.05***	3.79***
Profit loss by level of soil fertility[c]				
Fertile locations	160	14851.80	2812.38	0.83
Less fertile location	220	13271.13	4076.81	0.73
t-ratio (Fertile vs. less fertile)		2.25**	-7.83***	6.94***
Profit loss by level of off-farm income				
None or < 40% of off farm income share	290	14333.40	3386.07	0.78
Off farm income share of ≥ 40%	90	12658.36	4054.67	0.72
t-ratio (Low vs. high off-farm share)		2.05**	-3.36***	3.63***
All farms	380	13936.68	3544.42	0.77

Note: [a] Estimate of loss from maximum profit obtainable given prices and fixed factor endowments. Maximum profit per hectare is computed by dividing the actual profit per hectare of individual farms by its efficiency score.

[b] Developed infrastructure refers to score below the mean index value of infrastructure.

[c] Fertile location refers to score below the mean index value of soil fertility.

*** significant at 1 percent level (p<0.01)

** significant at 5 percent level (p<0.05)

* significant at 10 percent level (p<0.10)

Factors explaining inefficiency

The impact of the socio-economic factors accounting for this inefficiency in modern rice farming is listed in the lower panel of Table 2. Before discussing the results, we should first clearly state our prior expectations regarding the signs on these variables.

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[10] Profit-loss is defined as the amount that have been lost due to inefficiency in production given prices and fixed factor endowments and is calculated by multiplying maximum profit by (1 – PE). Maximum profit per hectare is computed by dividing the actual profit per hectare of individual farms by its efficiency score.

We expected that education, experience of growing modern rice, soil fertility, and extension would all be positively related to efficiency[11], while tenurial status, infrastructure (lack of), and percentage of non-farm income would be associated with lower efficiency levels. Results show that coefficients on the five of the seven variables are significantly different from zero with consistent expected sign.

Owner operators perform better than the tenants as expected. This is largely due to relatively higher input intensive nature of modern rice farming where owner-operators have incentives to invest more in terms of irrigation and other capital equipment compared to tenants. The input sensitivity of modern rice production, therefore, may result in lower efficiency when less than optimal level of investment is made as with the case of tenants. It was observed that the tenants made significantly higher profit-loss due to significantly lower level of profit efficiency (Table 5).

The poor effect of education in modern rice farming is not surprising. Similar results have been reported in past analyses of technical efficiency in Bangladeshi agriculture (for example see Wadud and White, 2000; Deb, 1995). The average education levels of less than four years (see Table 1) help explain the education result. However, Table 5 still reveals that farmers with no education incur significantly higher profit loss and perform at significantly lower level of profit efficiency although the effect is not captured in the regression analysis.

Experience in growing modern rice varieties pay-off well as expected. Farmers with more than three years of experience in growing modern varieties earn significantly higher profit, incur less profit-loss and operate at significantly higher level of profit efficiency (Table 5).

The extension service (weakly significant at 15% level), which is particularly aimed at diffusing modern rice technology to the farmers, seemed to play its part in increasing efficiency in modern rice production although it reached only a fraction of the total farming population (see Table 1). Table 5 again clearly reveals that farmers who have access to extension services perform significantly better in terms of earning actual profit, incurring less profit loss and operating at higher level of efficiency.

The modern rice producer benefits significantly from better infrastructure. It is evident that badly developed infrastructure has negative effects on both technical and allocative inefficiency. Technical efficiency would be adversely affected by not having inputs to use at the correct time, or not at all, and allocative efficiency would be affected by these constraints as well. This intuition is confirmed in Table 5, which clearly reveals that the incidence of incurring higher profit-loss subject to lower efficiency as well as low actual profit among the farmers in underdeveloped regions is significant.

Similarly, farmers located at fertile regions perform significantly better than their peers in less fertile regions, thereby reinforcing the argument that improvement in soil fertility is a crucial element in increasing profitability (Table 5).

The percentage of income earned off-farm was included to reflect the relative importance of non-agricultural work in the household. The positive sign on the estimated coefficient points towards a situation where those households who have higher opportunity to engage in off-farm work fail to pay much attention to their crops relative to other farmers. Table 5 clearly shows that households with off-farm income share of more than 40% in total household income operate at significantly lower levels of efficiency and hence earn less actual profit and incur high profit-loss.

Policy Implications

Results of this study clearly reveal that farmers in general are highly responsive to changes in output price as well as prices of major inputs, such as labour, animal power services and fertilizers.

Profitability increases substantially with increase in land area under cultivation. This is expected in a land scarce country like Bangladesh where per capita cultivable land is only 0.06 ha (BBS, 2001).

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[11] A negative sign on the coefficient indicates positive impact on efficiency except for the infrastructure variable.

Such high demand for agricultural land has given rise to an exploitative tenurial structure where land rent accounts for as high as 40% of gross value of rice output (Hossain, et al., 1990). Present study clearly reveals that tenants indeed operate at lower level of efficiency as compared to the owner operators. Also, long years of experience of modern rice farming helps farmers to allocate modern inputs effectively, thereby allowing them to operate at higher level of efficiency. It is however, surprising that after three decades of widespread diffusion of this ‘Green Revolution’ technology, there are farmers who have adopted modern rice farming only recently (less than three years ago), indicating bottlenecks that exists in technology diffusion and subsequent adoption. This intuition is reinforced by the fact that the few farmers who had contact with extension services, whose primary aim is to promote modern technology diffusion, operate at a very high level of efficiency (90%). This result is sufficient to make a strong case in favour of strengthening the agricultural extension system to promote farmer welfare. Influence of rural infrastructure in improving efficiency is also clearly evident in this study. Poor rural infrastructure has been identified as one of the major impediments to agricultural development in Bangladesh (Ahmed and Hossain, 1990). Improved access to input markets and services enables farmers to adjust their resources relatively more effectively, such as timely availability of fertilizers and pesticides at competitive prices, thereby positively influencing profitability. Soil fertility, an inherent capacity of the cultivable land, is also an important factor in promoting farmers’ welfare. Criticism of adverse effect of ‘Green Revolution’ technology on the environment is on the rise. For example, Singh (2000) identified widespread adoption of ‘Green Revolution’ technologies as a cause of significant soil degradation in Haryana state of India. Our result reveals that farmers located in fertile soil regions perform significantly better than those in less fertile regions. This calls for a coordinated effort to promote effective soil fertility management, for example through moderating crop mixes, input use adjustments, particularly chemicals, and directly undertaking soil conservation practices. This again points towards justification in favour of strengthening extension services equipped with skills that can address a broader development agenda. Lastly, poor performance of farmers with increased opportunity to earn from off-farm sources indirectly establishes that farming is becoming a secondary activity and is incapable of providing returns sufficient to maintain livelihood even in a rural setting. Development of rural infrastructure will exert a dual effect by improving farmers’ earnings for those who concentrate on farming as a primary activity and also opening up opportunities to earn from off-farm sources to make both ends meet.

CONCLUSIONS

The study used stochastic profit frontier functions to analyse production efficiency of Bangladeshi modern rice farmers. Using detailed survey data obtained from 380 modern rice farms spread over 21 villages in 1997 we obtain measures of profit inefficiency with wide variation among farmers. The mean level of efficiency for modern rice farming is 0.77 indicating that there remains considerable scope to increase profits by improving technical and allocative efficiency.

The farm-specific variables used to explain inefficiencies indicate that those farmers who have more experience in growing these modern varieties, better access to input markets, located in fertile regions, and those who do less off-farm work tend to be more efficient. Owner operators are clearly more efficient than the tenants. Extension services have a positive influence in increasing efficiency in modern rice farming.

The policy implications are clear. Inefficiency in farming can be reduced significantly by improving rural infrastructure and strengthening extension services. Also, measures to promote effective soil fertility management will improve efficiency. Land reform measures aimed at promoting land ownership will have a positive role in increasing efficiency of these modern rice producers who will ultimately be put under pressure to provide food for the rapidly growing urban population in the coming years in Bangladesh.

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APPENDIX

The Translog Profit Function

$$\ln \pi' = \alpha_0 + \sum_{j=1}^{5} \alpha_j \ln P'_j + \tfrac{1}{2} \sum_{j=1}^{5} \sum_{k=1}^{5} \tau_{jk} \ln P'_j \ln P'_k + \sum_{j=1}^{5} \sum_{l=1}^{2} \phi_{jl} \ln P'_j \ln Z_l$$
$$+ \sum_{l=1}^{2} \beta_l \ln Z_l + \tfrac{1}{2} \sum_{l=1}^{2} \sum_{t=1}^{2} \varphi_{lt} \ln Z_l \ln Z_t \qquad (A1)$$

Variables are defined in the text.

The corresponding share equations are expressed as,

$$S_j = -\frac{P_j X_j}{\pi} = \frac{\partial \ln \pi'}{\partial \ln P'_j} = \alpha_j + \sum_{k=1}^{5} \tau_{jk} \ln P'_k + \sum_{l=1}^{2} \phi_{jl} \ln Z_l \qquad (A2)$$
$$S_y = \frac{P_y X_y}{\pi} = 1 + \frac{\partial \ln \pi'}{\partial \ln P_y} = 1 + \sum_{j=1}^{5} \alpha_j + \sum_{j=1}^{5} \sum_{k=1}^{5} \tau_{jk} \ln P'_j + \sum_{j=1}^{5} \sum_{l=1}^{2} \phi_{jt} \ln Z_l \qquad (A3)$$

where S_j is the share of *j*th input, S_y is the share of output, X_j denotes the quantity of input *j* and *Y* is the level of rice output. Since the input and output shares form a singular system of equations (by definition S_y - ΣS_j = 1), one of the share equations, the output share, is dropped and the profit function and variable input share equations are estimated jointly using SURE procedure in Intercooled Stata Version 7. Parameter estimates are presented in Table A1.

Profit elasticities

The profit elasticity with respect to changes in input prices is defined as: $\frac{\partial \ln \pi'}{\partial \ln P'_j}$

The profit elasticity with respect to changes in fixed inputs is defined as: $\frac{\partial \ln \pi'}{\partial \ln Z_l}$

The profit elasticity with respect to changes in output price is defined as: $\frac{\partial \ln \pi'}{\partial \ln P_y}$

Table A1. Joint estimation of translog profit function with variable input shares.

Variables	**Parameters**	**Coefficients**	**t-ratio**
Profit function[a]			
Constant	α_0	8.8137	23.23 ***
$\ln P'_F$	α_F	0.0356	0.58
$\ln P'_W$	α_W	0.0137	0.08
$\ln P'_M$	α_M	-0.0856	-1.01
$\ln P'_S$	α_S	0.1407	2.54 ***
$\ln P'_P$	α_P	0.0210	0.38
½$\ln P'_F$ x $\ln P'_F$	τ_{FF}	-0.1882	-10.00 ***
½$\ln P'_W$ x $\ln P'_W$	τ_{WW}	-0.2459	-4.95 ***
½$\ln P'_M$ x $\ln P'_M$	τ_{MM}	-0.0627	-3.70 ***
½$\ln P'_S$ x $\ln P'_S$	τ_{SS}	-0.1039	-5.17 ***
½$\ln P'_P$ x $\ln P'_P$	τ_{PP}	-0.2861	-2.05 **
$\ln P'_F$ x $\ln P'_W$	τ_{FW}	-0.0125	-0.81
$\ln P'_F$ x $\ln P'_M$	τ_{FM}	0.0154	1.43
$\ln P'_F$ x $\ln P'_S$	τ_{FS}	-0.0074	-0.59
$\ln P'_F$ x $\ln P'_P$	τ_{FP}	-0.0843	-6.39 ***
$\ln P'_W$ x $\ln P'_M$	τ_{WM}	-0.0223	-1.01
$\ln P'_W$ x $\ln P'_S$	τ_{WS}	-0.0433	-2.65 ***
$\ln P'_W$ x $\ln P'_P$	τ_{WP}	-0.0227	-0.79
$\ln P'_M$ x $\ln P'_S$	τ_{MS}	-0.0154	-1.29
$\ln P'_M$ x $\ln P'_P$	τ_{MP}	0.0005	0.03
$\ln P'_S$ x $\ln P'_P$	τ_{SP}	-0.2527	-1.79 *
$\ln P'_F$ x $\ln Z_L$	ϕ_{FL}	0.0005	0.07
$\ln P'_F$ x $\ln Z_A$	ϕ_{FA}	0.0072	1.85 *
$\ln P'_W$ x $\ln Z_L$	ϕ_{WL}	0.0532	2.96 ***
$\ln P'_W$ x $\ln Z_A$	ϕ_{WA}	0.0387	3.70 ***
$\ln P'_M$ x $\ln Z_L$	ϕ_{ML}	-0.0026	-0.31
$\ln P'_M$ x $\ln Z_A$	ϕ_{MA}	0.0158	3.20 ***
$\ln P'_S$ x $\ln Z_L$	ϕ_{SL}	0.0060	1.31
$\ln P'_S$ x $\ln Z_A$	ϕ_{SA}	0.0049	1.82 *
$\ln P'_P$ x $\ln Z_L$	ϕ_{PL}	0.0148	3.40 ***
$\ln P'_P$ x $\ln Z_A$	ϕ_{PA}	0.0029	1.14
$\ln Z_L$	β_L	0.9457	9.29 ***
$\ln Z_A$	β_A	-0.1133	-1.55
½$\ln Z_L$ x $\ln Z_L$	φ_{LL}	-0.0148	-0.61
½$\ln Z_A$ x $\ln Z_A$	φ_{AA}	0.0044	0.49
$\ln Z_l$ x $\ln Z_A$	φ_{LA}	-0.0168	-1.46
Adjusted R-squared (from OLS)		0.83	
Chi-squared (35 d.f.)		812.69***	
Number of observations		380	

Note: [a] Only profit function estimates are reported due to space limitation.

*** significant at 1 percent level ($p<0.01$)

** significant at 5 percent level ($p<0.05$)

* significant at 10 percent level ($p<0.10$)