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Access to Microfinance: Does it Matter for Profit Efficiency among Small Scale Rice Farmers in Bangladesh?

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Abstract: This paper measures profit efficiency and examines the effect of access to microfinance on the performance of rice firms in Bangladesh. An extended Cobb-Douglas stochastic frontier profit function was used to assess profit efficiency and profit loss of rice farmers in Bangladesh in a survey data of 360 farms throughout the 2008-2009 growing seasons. Model diagnostics reveal that serious selection bias exists that justifies the uses of sample selection model in stochastic frontier models. After effectively correcting for selectivity bias, the mean profit efficiency of the microfinance borrowers and non-borrowers were estimated at 68% and 52% respectively, thereby suggesting that a considerable share of profits were lost due to profit inefficiencies in rice production. The results from the inefficiency effect model show that households' age, extension visits, off-farm income, region and the farm size are the significant determinants of inefficiency. Some indicative policy recommendations based on these findings have been suggested.

Key words: Stochastic frontier function · Profit efficiency · Selection bias · Bangladesh · Microfinance

INTRODUCTION

Bangladesh is predominately an agrarian country with over 53% of its 140.6 million population engaged in agriculture [1]. Agriculture accounts for 21% of the gross domestic product (GDP) and 50% of overall employment [2]. The economic prosperity of the country also depends upon sustained growth in agricultural production and productivity. Agricultural productivity is linked to farm profitability. Improved productivity may provide increasing revenues and lower unit costs also for resource limited rice farmers in Bangladesh [3]. Productivity and income improvements are, however, dependent upon access to sufficient financial capital. Impoverished farmers in Bangladesh generally have to raise loans from money lenders who charge exorbitant interest rates. There is a huge gap between the need for credit and the availability of affordable credit sources. Consequently, poor smallholders may be perpetually trapped in poverty due to the lack of funds needed for undertaking the purchases of variable inputs and productive investments in farming [4]. For these financially constrained but economically active poor people, microfinance has emerged as a substitute for informal credit[1] [5]. Despite the fact that profitability of agriculture is generally low and interest rates from informal credit sources are high, it is possible for microfinance providers to operate on a cost covering basis and to offer financial services to farmers at the reasonable interest rates that contribute to improving productivity and profit efficiency.

The success of microcredit has been well reported in several studies in broad areas such as poverty alleviation [6], group-based lending [7,8], women's empowerment [9, 10] and sustainability and outreach [11,12]. Nevertheless, providers of micro credits have not generally addressed the credit needs of small and marginal farmers[2] for certain perceived problems, which include *inter alia* the risk of investment in agriculture, seasonality of agricultural production, poor loan repayment performance and the technical nature of agricultural production [13]. Thus, the analysis of effects of microfinance on efficiency and productivity of agriculture

[1]It is characterized by informal financial alternatives such as village money lenders, traders, friends, relatives, shopkeepers; landlords who provide limited amounts of money that are rigidly administered.
[2]According to loan providing institutions in Bangladesh, marginal and small farmers operate land areas between 0.2 to1 hectares. (PKSK and IFAD, 2004).

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is largely missing. We expect that inadequate funding of poor farmers has a negative impact on agricultural productivity and efficiency of small farms.

Although considerable efforts have been focused on measuring rice production efficiency in Bangladesh [14-18], little attention has been paid to studying the relationships of market indicators, financing and household characteristics on the production and profit efficiency of farms. This contrasts with the large number of such studies in other developing and developed countries [19-22]. Only recently Rahman [23] estimated the profit efficiency of Bangladeshi rice farms by concentrating on cultivation of modern rice varieties and reported a mean efficiency of 77%. The efficiency differences were largely explained by infrastructure, soil fertility, experience, extension services, tenancy status and by the share of non-agricultural income. Using a nationally representative survey of 16 villages, Hossain [24] estimated the allocative efficiency of rice producers. However, the data of that study dates back to 1982. In the present study, we incorporated the whole rice production on farms in the profit efficiency analysis by assuming that the economic situation of farmers is better represented by the aggregated crop production. Moreover, we believe that our dataset on Bangladesh's agriculture is contemporary which is based on a random sample from a widely dispersed geographic region.

The main objectives of this study are to estimate the contribution of microfinance on profit efficiency and to measure the absolute profit-loss incurred by rice farmers in Bangladesh. In the analysis, we apply a recently developed approach by Greene [25,26], which provides a general framework for testing and taking into account the sample selection in the stochastic (profit) frontier function analysis. In addition, we identify the determinants of profit inefficiency and estimated profit loss at the farm level separately for microfinance borrowers and non-borrowers. This paper contributes to the growing literature on the impact of microfinance by estimating its effect on profit efficiency of rice growing farms in Bangladesh. We also suggest that agricultural development policy can strengthen the links between financial development, agricultural productivity and profit efficiency by focusing on agricultural microfinance. The paper is organized as follows: Section 2 presents the concepts of profit efficiency and gives the theoretical background of sample selection. Section 3 deals with the data and the study areas. Section 4 deals with the empirical model. Section 5 discusses the results of the study. Section 6 concludes and provides some recommendations.

Analytical Framework: The analysis of the effect of a specific treatment like the participation to microfinance cannot be estimated directly by comparing participating and non-participating groups if there is sample selectivity The typical approach "to control and test for selection bias" is to fit the probit model for the sample selection equation and then using the selected sample, fit the second step model (Ordinary least squares or Weighted Least Squares) by appending the inverse mills ratio ($\hat{\lambda}_i$) from the first step as an independent variable to correct for selectivity bias in the second step and to test its significance. Greene ([25], [26]), however, claims that such a specification is not appropriate in non-linear models. The reasons are: (a) the impact on the conditional mean of the model under consideration will not necessarily take the form of inverse mills ratio (IMR) since $\hat{\lambda}_i$ arises as $E[\varepsilon_i | d_i = 1]$ in linear models only, (b) the bivariate normality assumption needed to justify the inclusion of IMR does not even appear in the original model and (c) the distribution of the observed dependable variable conditioned on the selection will not be what it was without the selection. Thus, one cannot just add the IMR. Greene [26], proposed the following internally consistent method of incorporating the 'sample selection' into a stochastic frontier model:

Sample selection:

$$d_i^* = \alpha' z_i + w_i, d_i = 1, d_i^* > 0, w_i \sim N[0,1] \tag{1}$$

Stochastic frontier:

$$y_i = \beta' x_i + v_i - u_i \tag{2}$$

(y, x) is observed only when d =1

Error structure:

$$v_i - u_i = \varepsilon_i, \varepsilon_i \sim N[0, \sigma_\varepsilon^2]$$
$$u_i = \sigma_u \, | U_i |, \text{where} U_i \sim N[0,1]$$
$$v_i = \sigma_v V_i, \text{where} V_i \sim N[0,1]$$
$$(w_i, v_i) \text{~bivariate normal with } [(0,1),(1, \rho\sigma_\sigma, \sigma_v^2)]$$

The Greene's model assumes that the unobserved characteristics in the selection model correlate with the noise term in the stochastic frontier function. In Equation (1) d_i^* is a probit selection equation and y the stochastic frontier function, specified only for the selected group. z-variables represent characteristics that determine the participation in the selected group, w being the error term, x is a matrix of explanatory variables of the stochastic frontier function, v is the two sided random error (statistical disturbance term), independent of the u, that permits for random variations in output due to factors such as weather, omitted explanatory variables, measurement errors in y and other exogenous shocks, u is the one sided non-negative error term (e.g. farm specific profit inefficiency). The estimator of the above equations is documented in earlier studies [25-27].

In addition to the selection equation, we have to specify the stochastic profit frontier function. Ali and Flinn [20] have stated that when farmers face different prices and have different factor endowments (in the short term analysis), it may not be appropriate to use a production function to measure efficiency. This has led to the application of stochastic frontier profit functions in the estimation of farm specific efficiency [19, 20, 28]. Lau and Yotopoulos [29] popularized the use of the profit function approach in which farm specific prices and fixed factors are incorporated in the analysis of economic efficiency.

We assume that input prices $(w \in R^N_{++})$ and output prices $(p \in R^M_{++})$ are exogenous although not the same for all producers, who seek to maximize (frontier) profit by choosing the variable input vector $x \in R^N_+$ that is required to produce an output vector $y \in R^M_+$. The standard against which the performance of a farm can be measured, is its potential to maximize profit, i.e. to operate at a point of the frontier where the marginal product of each input equals price ratio of input and output. It is given by:

$$\pi^* = py^* - wx^* \tag{3}$$

The profit efficiency approach takes into account the effect of technical, allocative and scale inefficiencies in the profit relationship and also any deviations from the optimal production that would lead to lower profits for the enterprise [30]. Profit efficiency is defined as the capability to achieve optimal performance with respect to profits for given sets of prices and technologies (the level of fixed factors of the farm). In contrast, profit inefficiency is defined as the loss of profit due to not operating at the optimum level [20]. When some of the inputs are fixed and the producer adjusts the variable inputs and outputs to maximize the variable profit, it is possible to define a variable profit function (variable profit = the total return - the variable costs) as:

$$v\pi_i(P_i, Z_i) = P_i \cdot Y(X_i, G_i) - \sum W_i X_i \tag{4}$$

where Y (.) is the production function, P and W are the output price and the variable input prices and G is the vector of fixed inputs. Normalization of the variable profit and prices by one price (in this case output) imposes linear homogeneity of the profit function with respect to output and input prices. It follows that the normalized profit function which is well-behaved[3] can be written as:

$$\begin{aligned} \frac{v\pi_i(P_i, G_i)}{P_i} &= \frac{P_i \cdot Y(X_i, G_i) - \sum W_i X_i}{P_i} \\ &= Y(X_i, G_i) - \frac{\sum W_i X_i}{P_i} = Y(X_i, G_i) - \sum P_i' X_i \end{aligned} \tag{5}$$

$P_i' = \frac{W_i}{P_i}$, is the normalized price of input X_i

To our knowledge, the Greene's model of Equation 2 is only defined for the Aigner-Lovell-Schmidt [31] model. Thus, the model can be used for assessing possible selection bias, but it does not include the determinants of inefficiency. Therefore, we compare the results of this stochastic frontier model (jointly estimated with probit selection equation) to that of stochastic profit frontier with inefficiency effects model of Battese and Coelli [32]. The comparison takes place in the specified group, not simultaneously in the whole sample. In the equation 2, the stochastic variable profit frontier with inefficiency is defined as:

$$v\pi_i / P_i = \pi_i' = f(P_{ij}', G_{ik}) \exp(\xi_i) \tag{6}$$

where, $v\pi_i /Pi$ is the normalized variable profit of the i^{th} farm, computed as the gross revenue minus the variable cost, divided by farm specific output price Pi ; P_{ij}' is the price of j^{th} variable input on i^{th} farm divided by the output price; G_{ik} is the level of k^{th} fixed factor for the i^{th} farm and ξ_i is the random error term. The error term, ξ_i, is assumed to be decomposable [20] for frontier profit function, as presented in Equation 2.

In the inefficiency effect model of Battese and Coelli [32], it is assumed that farm-specific determinants affect the mean of efficiency, the variances being homogenous (in the group of d = 1 (or d = 0). The $u_i s$ are assumed to be independently distributed as truncations at zero of the normal distribution with a mean $\mu_i = \delta_0 + \sum_d \delta_d M_{di}$ and

[3]The normalized restricted profit function is non-increasing input prices (w) and non-decreasing in G, convex and twice continuously differentiable in G.

variance σ^2_u, where M_{di} are the variables representing socio-economic characteristics of i^{th} farm to explain inefficiency and δ_o,δ_d are unknown parameters to be estimated. The profit efficiency of i^{th} farm in this context is given by:

$$PE_i = \exp\{-u_i\} = \exp\left\{-\delta_0 - \sum_{d=1}^{D}\delta_d M_{di} - \vartheta_i\right\}, \qquad (7)$$

Battese and Coelli [32] model is estimated applying maximum likelihood estimates (MLE) with simultaneous estimation of the stochastic frontier and inefficiency effects and individual specific (with respect to ξ_1) conditional expected (E) efficiency (u_i) values are estimated according to

$$E[\exp(-u_i)|\xi_i] = \left[\exp\left\{-\mu_{*i} + \frac{1}{2}\sigma_*^2\right\}\right].\left[\frac{\Phi\left[(\mu_{*i}/\sigma_*) - \sigma_*\right]}{\Phi(\mu_{*i}/\sigma_*)}\right]$$

where $\mu_{*i} = \dfrac{\sigma_v^2(\delta_d M_{di}) - \sigma_u^2(\vartheta_i)}{\sigma_v^2 + \sigma_u^2}, \sigma_*^2 = \dfrac{\sigma_v^2\sigma_u^2}{\sigma_v^2 + \sigma_u^2}$

σ_*^2 denotes the total variation in the dependent variable due to technical inefficiency (σ_u^2) and to random shocks (σ_v^2) combined.

Greene [26] applies maximum simulated likelihood in the estimation of selectivity-efficiency model. Conditional farm specific efficiency estimates can be estimated either by simulations or applying Jondrow *et al.* [33] approach. The farm-specific profit inefficiency (PI) index can be obtained by the following equation

$$PI = (1 - \exp[-u_i]) \qquad (8)$$

Profit-loss (PL) is defined as the amount of profit that has been lost due to the inefficiency given the farm specific prices and fixed factor endowments. Maximum profit per hectare is calculated by dividing the actual profit per hectare of individual farms by their respective corresponding efficiency scores. Profit-loss is calculated by multiplying maximum profit per hectare by ($1-PE_i$), where PE_i is the profit efficiency score of the i^{th} farm.

Data and the Study Areas

Sample and Data: Primary data were collected through an intensive farm-survey of rice producers from a total of 12 villages of the north-west and north-central regions in Bangladesh between June-August 2009. These regions were selected on the basis of their high level of poverty and good agricultural potential as well as the presence of IFAD funded agricultural microfinance program. Microfinance institutions (MFIs) granted loans to the farmers based on their land holding criteria (0.2 to 1 hectare) although the land holding criteria was not strictly followed. The sample of the microfinance borrowers were randomly selected without replacement from the lists that were made available from the local offices of MFIs. The selection of non-borrowers was based on similar land and socio-economic characteristics that provided a control group for the analysis. Personal interviews were conducted for both borrowers and non-borrowers of microfinance. Data were collected from the farmers that produced Boro, Aman and Aus rice crops. A multistage proportional random sampling technique was used to obtain the study data from a total of 360 farm households. Half of the households were members of the microfinance program and the other half was non-members. In calculating profit efficiency, however, we considered 350 sample farms that obtained positive variable profit. The negative values of profit cannot be transformed to logarithmic values.

Variable Construction: Output was defined as the market value of the aggregated rice production. Rice output prices were gathered from individual farms. All rice (Boro, Aman, Aus) crops produced on the sample farms were aggregated into one output value, which was expressed in Taka[4]. Land (Z_L) represented the total amount of land (own-cultivated land, sharecropping land and rented/leased land) used for rice production and it was measured in hectares. Labor included both family (imputed for hired labor) and hired labor for pre and post planting operations and harvesting excluding threshing operations. The price (P_W) of labor was measured as the wage of hired labor per-day. Fertilizers included all fertilizers used and were measured in kilograms and the price (P_F) of fertilizer was the weighted average of all fertilizers purchased (in Taka/kg). Seeds included all seeds used and the price represented the average price (P_S) of seed (Taka/kg) used for rice cultivation. Irrigation covered the total area of irrigated land under rice. The price of irrigation (P_I) included the cost of irrigation per hectare of land. Capital was not included in the profit function since the capital lacked any significance when it was included in the models. Probably this is because of difficulties in the reliable measurement of capital and the fact that on many farms capital input was very low.

[4]USD 1= Taka 69. 42, Euro 1=Taka 91.74 (as of November 10, 2010)

Empirical Models: The stochastic profit function model with correction for sample selection is estimated. Therefore, the decision to participate in the microfinance program has been modeled. The decision of the i^{th} farm to participate in microfinance program is a function of farmers' socio-economic characteristics as well as some criteria set by the MFIs to select borrowers. The decision of the i^{th} farm to participate in the microfinance program is described by an unobservable selection criterion function, H^*. The model[5] is specified as follows:

$$H^* = a'Z_i + w_i \quad (9)$$

$$H = 1 \text{ iff } H^* = a'Z_i + w_i \geq H = 0, \text{ otherwise}$$

where, Z is a vector of variables explaining the participation in the microfinance program, α is a vector of parameters to be estimated, w is the error term distributed as w. However, we do not observe the selection criterion function, but a dummy variable, H, is observed. The dummy variable, H, takes a value of 1 if the farm participates in the microfinance program and 0 otherwise.

As a second step, the frontier profit function for microfinance participants is estimated. The functional form of the stochastic frontier profit function was determined by testing the adequacy of the more restrictive functional forms against the full transcendental logarithmic (translog) function. The model was chosen based on the likelihood ratio[6] (LR) test. The full translog profit frontier function is defined as:

$$\ln\pi' = \alpha_0 + \sum_{j=1}^{4}\alpha_j \ln p'_j + 1/2\sum_{j=1}^{4}\sum_{k=1}^{4}\beta_{jk}\ln p'_j \ln p'_k$$
$$+\sum_{j=1}^{4}\sum_{l=1}^{1}\omega_{jl}\ln p'_j \ln G_l + \psi_l \ln G_l + \varphi_l(\ln G_l)^2 + v_i - u_i, \text{ iff H=1} \quad (10)$$

where π' is the restricted normalized profit (total revenue minus total cost of variable inputs) of the i^{th} farm normalized by the rice output price (P_y); *ln* is the natural logarithm, P'_j is the price of the j^{th} input (P) normalized by the rice output price (P_y); j_1 is the labor wage (total expenditure of hired labor divided by the output price); j_2 is the seed price; j_3 is the fertilizer price; j_4 is the irrigation price; G_l is the quantity of fixed inputs; l_1 is the areas under rice production; v is the two sided random error and u is the one sided non-negative error term. In the stochastic frontier model, taking the sample selection into account, it is assumed that the error term (w) of equation (9) is correlated with the error term (v) of equation (10) and therefore, (v,w)~bivariate normal with $[(0,1),(1,\rho\sigma_v,\sigma_v^2]$.

The explanatory variables for the participation of microfinance include farmers' socio-economic characteristics and environmental variable. The probit selection model was used to estimate the probability that a household participates in the microfinance program. The model includes the following variables: age of the head of household, the farm size, household wealth, household savings and the distance to credit facility. Since the variables in the probit selection equation and in the stochastic profit frontier differ, the structural model (i.e. outcome equation) satisfies the identification criterion [25, 26, 27, 35, 36].

In the stochastic frontier with inefficiency effect model (equation 7), M_d includes the variables representing socio-economic characteristics of the farm to explain inefficiency: d_1 is the age of the head of the farm household; d_2 is the education of the farm household head; d_3 is the family size; d_4 is the off-farm income share out of total farm income; d_5 is the extension visits (no. of contacts); d_6 is the region (dummy variable to account for the variations at inter-regional level with respect to physical and environmental factors on profit efficiency. The value is 1 if the farmer was located in the north-central region and 0 otherwise); d_7 is the farm size; d_8 is the distance of home to market and ϑ_i is the two sided random error term.

RESULTS AND DISCUSSION

Table 1 presents the summary statistics (mean and standard deviation) of the output and inputs used in the analysis and other, relevant to the inefficiency effect model, variables. Household characteristics are broken down by the microfinance borrowing status. The figures show that, there are no significant differences between the two groups in terms of output and the level of input use except for the irrigation cost. Non-borrowers have larger land holdings (1.35 hectares) than the borrowers

[5] Similar sample selection procedure in the context of stochastic frontier models was applied by Rahman *et al.* [27] in modeling production efficiency of Jasmine rice producers in Thailand.

[6] The likelihood-ratio test statistic, LR = -2{ln[likelihood (H_0)-ln[likelihood(H_1)]}, has approximately χ_v^2 distribution with v = number of parameters assumed to be zero in the respective null hypotheses, (H_0). To conduct tests involving γ parameter, the critical value of the $\chi^2$is taken from Kodde and Palm [34]

(1.11 hectares) and the borrowers had incurred significantly higher irrigation price per hectare land. However, among the socio-economic and institutional factors, significant differences exist between the two groups. For example, the proportion of microfinance borrowers' utilizing extension services is significantly higher than the non-borrowing farm households. The result is consistent with a priori expectations that microfinance borrowers are assumed to make frequent interactions with in-field trainers from loan providing institutions along with the visits of the extension officers of the government. On the other hand, non-borrowers are significantly older and more experienced. The two groups did not differ significantly in terms of family size, education or off-farm income share.

The results of the probit selection equation are presented in Table 2. First, to model the selection equation and to obtain the results with which the outcome equation (equation 10) was compared, binary probit regression was used with participation in microfinance program as the dependent variable and five independent variables entered into to the regression equation. The chi-squared test statistic in the probit selection equation is statistically significant at 1% level that confirms the joint significance of the relationship between the explanatory variables and participating in microfinance program. Seventy-two percent of the observations were predicted accurately. Among the variables representing household characteristics, age of household head significantly decreases the probability of being in the microfinance

Table 1: Summary statistics of the variables used in the analysis

	Microfinance borrowers (N= 176)		Non-borrowers of microfinance (N= 174)		
Variables	Mean	SD	Mean	SD	t-ratio
Output (kg)	6532.21	6515.09	7032.14	8759.57	-0.60
Profit (taka)	44105.15	47407.23	44647.38	60232.99	-0.09
Rice price (taka/kg)	13.53	2.98	13.35	3.17	0.54
Land cultivated (ha)	1.11	1.20	1.35	1.90	-1.40
Labor wage (Taka/day)	149.91	42.28	149.76	49.15	0.03
Seed price (taka/kg)	57.33	52.88	63.00	55.32	-0.97
Fertilizer price (Taka/kg)	22.70	8.25	22.76	8.92	-0.06
Irrigation price (Taka/ha)	6160.97	4476.32	7348.20	5902.32	-2.14**
Farm-specific variables					
Age (years)	40.67	10.99	43.93	14.14	-2.38**
Family Size (no.)	4.51	1.79	4.70	1.78	-0.98
Education (Years)	4.99	4.52	5.04	4.98	-0.09
Extension (%)	80.23	39.94	65.46	47.06	3.13***
Off-farm income share (%)	33.78	24.74	36.76	28.25	-1.04
Experience (years)	21.67	12.06	24.92	14.50	-2.25**

Note: SD, standard deviation

Table 2: Parameter estimates of probit selection equation: probability of being in the microfinance program

	1 (Participation in microfinance program)	
Variables	Coefficient	t-ratio
Constant	1.09	3.97***
Age of head of household (years)	-0.015	-2.74***
Farm size	-0.00036	-1.68*
Wealth (Taka)	-0.824	-2.64**
Household savings (Taka)	0.646	3.23***
Distance to credit facility (km.)	-0.254	-3.58***
Model diagnostics		
Log likelihood	-221.71	
McFadden R-squared	0.086	
Chi-squared	41.78	
Degrees of freedom	5	
Accuracy of prediction (%)	71.59	
Number of total observations	350	

***Significant at 1% level (P<0.01); **Significant at 5% level (P<0.05); *Significant at 10% level (P<0.1). The function 1(.) is an indicator function equal to one if the condition is true and zero otherwise.

Table 3: MLE of stochastic profit frontier model for microfinance participants

	Stochastic profit frontier model (jointly estimated with probit selection equation)			Conventional stochastic profit frontier with inefficiency effects model		
Variables	Parameters	Coefficient	t-ratio	Parameters	Coefficients	t-ratio
Constant	α_o	9.397	5.75***	α_o	9.213	12.79***
$\ln P'_W$	α_w	-0.027	-0.02	α_w	-0.526	-0.87
$\ln P'_S$	α_s	-0.096	-0.48	α_s	-0.187	-1.39
$\ln P'_F$	α_F	-0.478	-1.60	α_F	-0.580	-3.45***
$\ln P'_I$	α_I	-0.262	-3.82***	α_I	-0.149	-3.03***
$1/2(\ln P'_W \ln P'_W)$	β_{ww}	0.102	0.39	β_{ww}	0.145	1.14
$1/2(\ln P'_S \ln P'_S)$	β_{SS}	0.004	0.06	β_{SS}	0.049	1.10
$1/2(\ln P'_F \ln P'_F)$	β_{FF}	0.411	1.51	β_{FF}	0.417	2.90***
$1/2 \ln(P'_I \ln P'_I)$	$\beta\backslash$	0.006	0.12	β_{II}	-0.015	-0.48
In LnG_L	ψ_L	0.847	14.33***	ψ_L	0.911	17.76***
$1/2(\ln G_L \ln G_L)$	φ_{LL}	-0.118	-2.54**	φ_{LL}	-0.043	-1.09
Variance parameters						
σ_u		0.528	2.07**		-	-
σ_v		0.652	5.67***		-	-
Selectivity bias ($\rho_{w,v}$)		-0.978	-24.11***		-	-
$\gamma = \sigma_u^2/(\sigma_u^2+\sigma_v^2)$		-	-	$\gamma = \sigma_u^2/(\sigma_u^2+\sigma_v^2)$	0.88	37.59***
Log likelihood		-250.395			-103.02	
Inefficiency Function						
Constant		-	-	δ_0	-0.810	-0.82
Age		-	-	δ_1	-0.049	-2.11**
Education		-	-	δ_2	0.025	0.60
Family size		-	-	δ_3	-0.138	-1.20
Off-farm income		-	-	δ_4	6.144	3.94***
Extension visits		-	-	δ_5	-0.106	-2.69***
Region		-	-	δ_6	-2.067	-3.11***
Farm size		-	-	δ_7	0.003	3.55***
Distance to market		-	-	δ_8	-0.096	-0.65
Number of selected observations		176			176	

Notes: Figures in parentheses are asymptotic *t*-ratios. W, labor; F, fertilizer; S, seed; I, irrigation, L, Land.

*, **, *** Significant at 10% ($P<0.10$), 5 % ($P<0.05$) and 1% ($P<0.01$) level.

program, as expected. Similarly, farm size, household wealth and distance to credit facility significantly depress the probability to participate in microfinance program. Household savings, as a proxy for welfare status, confirms that the households' savings significantly increase the probability of participating in the microfinance program. The implication is that a better household saving scope affects their decision to participate in the microfinance program in the sense that households' saving accumulated through their past earnings boosts their confidence to comply with the rigidly administered loan repayment obligations.

Table 3 presents the results of the stochastic profit function corrected for selection bias (columns 3 and 4). Under the selectivity bias correction model, the coefficients had expected signs. The irrigation price and land area (fixed input) are significant inputs influencing farm profitability. In the conventional model, however, the prices of fertilizer and irrigation as well as land are significant inputs influencing farm profitability. The estimates of both σ_μ and σ_v are significantly different from zero at the 1% risk level. The coefficient of the selectivity variable ($\rho_{w,v}$), is significantly different from zero at the 1% risk level, which confirms that a serious selection bias exits. This finding justifies the use of sample-selection framework. In other words, this result indicates that the estimation of profit frontier using only the microfinance participants provides biased estimates of productivity, which will then be passed on to the biased profit efficiency scores afterward.

Thus, the confidence in the estimates is improved with the sample selection model. For comparison purposes the same table presents the stochastic frontier profit function with inefficiency effects (columns 6 and 7), which is estimated directly in a single stage with the computer program FRONTIER 4.1 by Coelli [37]. Nlogit 4.0 [38], is applied in the estimation of the selectivity bias correction models.

For statistical justification we used a set of hypotheses for the model selection, inefficiency specification and inefficiency effects on the basis of Battese-Coelli model [32]. All the hypotheses were tested using the LR test statistics. The null hypothesis that extended Cobb-Douglas (i.e. including only additional quadratic terms) profit function is an adequate representation of rice production was rejected at the 5% risk level (LR statistic 18.80> $\chi^2_{10,0.95}$= 18.31). However, the more detailed analysis showed that in the case of full translog almost all the coefficients became insignificant. In addition, more complicated functional forms were to some extent unstable in the estimations. Therefore, we preferred extended Cobb-Douglas in our more detailed analysis. The second null hypothesis was that the profit inefficiency does not exist (i.e. $\gamma = 0$), was also rejected at the 5% risk level (LR statistic 135.56>$\chi^2_{10,0.95}$= 3.84). This implies that the profit inefficiency is significant in determining the level and variability of profit for the farms in the study areas. The third null hypothesis that (H_o : δ_0, = δ_1 = ...= δ_8 = 0) inefficiency effects are not present in the model, was also rejected at the 5% risk level (LR statistic 65.76> $\chi^2_{9,0.95}$= 16.92). This indicates that combined effects of these chosen variables on the level of profit inefficiency were statistically significant. Thus, it can be concluded that the variables in the profit inefficiency model contribute significantly to the explanation of the observed profit inefficiencies among the farmers. The results of the hypotheses thus indicate that the discrepancy between observed profit and frontier profit was due to the presence of allocative, technical and scale inefficiencies.

The distribution of profit efficiency estimates of the microfinance participants and non-participants corrected for selectivity bias as well as for the conventional stochastic profit frontier with inefficiency effects, are presented in Table 4. The table shows that the average profit efficiency of microfinance participants in the selectivity bias correction model is 7.7% (p<0.01) lower than in the conventional model. It is evident that the direct estimation of single equation stochastic profit frontier models for only microfinance borrowing farms

Tabe 4: Frequency distribution of farm-specific profit efficiency estimates

	Microfinance Participants		Non-participants	
Profit Efficiency estimates	Stochastic profit frontier (Corrected for selectivity bias)	Stochastic profit frontier with inefficiency effects (conventional model)	Stochastic profit frontier (Corrected for selectivity bias)	Stochastic profit frontier with inefficiency effects (conventional model)
≥ 0.90 ≤ 1.00	1	9	0	2
≥ 0.80 ≤ 0.90	23	89	8	41
≥ 0.70 ≤ 0.80	49	40	25	41
≥ 0.60 ≤ 0.70	55	13	28	35
≥ 0.50 ≤ 0.60	36	7	38	18
≥ 0.40 ≤ 0.50	10	6	26	10
≥ 0.30 ≤ 0.40	1	4	18	11
≥ 0.20 ≤ 0.30	1	4	16	5
≥ 0.10 ≤ 0.20	0	2	9	4
≥ 0.0 ≤ 0.10	0	2	6	5
Mean	67.87	75.57	51.58	65.14
Std dev	11.48	17.33	19.46	20.09
Minimum	23.85	1.68	6.27	4.76
Maximum	92.73	92.25	88.97	92.11
Mean difference		-7.7		-13.56
t-ratio for mean difference (selectivity model vs. conventional model)		-4.91***		-6.40***
t-ratio for mean difference between the two groups (bias corrected)	9.52***			
Number of observations	176	176	174	174

*** Significant at 1% risk level (P<0.01)

Table 5: Frequency distribution of profit loss[7] among microfinance participants and non-participants in the selectivity model

	Microfinance participants (N=176)			Non-participants of microfinance (N=174)		
Range of profit loss (Taka/ha)	Average actual profit per ha	Profit efficiency score	Number of farms	Average actual profit per ha	Profit efficiency score	Number of farms
0-10,000	34802	0.69	14	14422	0.74	2
10001-20,000	49218	0.72	64	35386	0.59	16
20001-30,000	47560	0.65	70	53443	0.61	50
30001-40,000	76603	0.68	16	49104	0.51	30
40001-50,000	77024	0.62	8	49396	0.50	33
50001-60,000	90739	0.60	2	40132	0.38	22
60001-70,000	135435	0.67	2	57329	0.42	10
70001-80,000	-	-	-	58578	0.40	7
80001-90,000	-	-	-	17367	0.17	2
90001-100000	-	-	-	-	-	0
≥100001	-	-	-	84753	0.38	2
Mean	52617	0.68		48681	0.52	
Std dev	26990	0.11		32504	0.19	
Minimum	760	0.24		1168	0.06	
Maximum	158891	0.93		203531	0.89	

t-ratio for mean difference (Actual profit per hectare) 1.23

t-ratio for mean difference (Average profit-loss per hectare) -10.11***

seems to have understated the inefficiency levels. For example, 51% (= 89/176) of the microfinance participants were operating on the profit efficiency level of 0.80-0.90 in the conventional model, whereas only 13% (= 23/176) of participants were found to operate at this level according to the selectivity bias correction model.

The mean difference between the efficiency scores of these two models (selectivity vs. conventional model) is significantly different. We also get similar results for the non-participants. For example, 24% (= 41/174) of the non-participants were operating between 0.80-0.90 profit efficiency level in the conventional model, whereas only 5% (= 8/174) were found to operate at the same level under the selectivity model. The mean difference between the efficiency scores of these two models (selectivity vs. conventional model) is also significantly different from zero. The results indicate that microfinance participants, under the selectivity model, had significantly higher profit efficiency compared to their non-participating counterparts and access to microfinance had a significant impact on the profit efficiencies of these farms.

The smallholder farmers in both groups exhibited a wide range of profit inefficiency ranging from 7% to 76% in the sample of microfinance participants while for the non-participants the inefficiency ranged from 11% to 94%. The mean profit efficiency of microfinance participants, corrected for selectivity bias, is estimated to be 68%, while for the non-participants the bias corrected mean profit efficiency score is 52%. The results show that microfinance participants exhibited 16% higher profit efficiency compared to their non-participant counterparts. The significant t-statistic on the rho coefficient (Table 3) also indicated that after controlling for all other observed characteristics, the farmers who chose to participate in microfinance program had higher profit efficiency than individuals with similar characteristics drawn randomly from the population. The large variation in profit inefficiency is not surprising and similar results were reported in other empirical studies. For example, Rahman [23] reported mean profit efficiency level of 77% (6-83%) for modern rice producers in Bangladesh. Ali and Flinn [20] reported mean profit efficiency level of 69% (range 13-95%) for Basmati rice producers of Pakistan, Punjab. Ali *et al.* [30] reported mean profit efficiency level of 75% (range 4-90%) for rice producers in North-West Frontier Province of Pakistan. Based on the results it can be deduced that considerable amount of profits can be realized by both groups by improving their technical, allocative and scale efficiency in Bangladesh with greater scope for the non-participating farms.

The distribution of the loss in profit is shown in Table 5. The estimation of profit-loss per hectare, given the technology, prices and fixed factor endowments revealed that the mean profit-losses of microfinance

[7]Profit-loss is the potential profit that has been lost due to inefficiency given farm specific prices and fixed factor endowments. It is calculated by multiplying maximum profit by profit inefficiency (1-PE). Maximum profit is calculated by dividing the actual profit per hectare of individual farm by its efficiency score.

Table 6: MLE of stochastic profit frontier model for non- participants of microfinance

	Stochastic profit frontier model (jointly estimated with probit selection equation)			Conventional stochastic profit frontier with inefficiency effects model		
Variables	Parameters	Coefficient	t-ratio	Parameters	Coefficients	t-ratio
Constant	α_0	10.795	3.71***	α_0	9.924	7.05***
$\ln P'_W$	α_w	-2.07	-0.83	α_w	-1.327	-1.12
$\ln P'_S$	α_s	0.425	1.83**	α_s	0.394	2.32**
$\ln P'_F$	α_F	-0.211	-0.58	α_F	-0.186	-0.99
$\ln P'_I$	α_1	-0.106	-1.12	α_1	-0.137	-2.47**
$1/2(\ln P'_W \ln P'_W)$	β_{WW}	0.472	0.90	β_{WW}	0.294	1.19
$1/2(\ln P'_S \ln P'_S)$	β_{ss}	-0.155	-2.23**	β_{ss}	-0.125	-2.15**
$1/2(\ln P'_F \ln P'_F)$	β_{FF}	0.010	0.03	β_{FF}	-0.060	-0.32
$1/2 \ln(P'_I \ln P'_I)$	β_{II}	0.027	0.30	β_{II}	-0.023	-0.48
In LnZ_L	Ψ_L	0.819	9.53**	Ψ_L	0.812	13.55***
$1/2(\ln G_L \ln G_L)$	φ_{LL}	-0.074	-1.30	φ_{LL}	-0.025	-0.61
Variance parameters						
σ_μ		1.050	9.11***			
σ_v		0.381	4.19***			
Selectivity bias ($\rho_{w,v}$)		0.408	0.94		-	-
$\gamma = \sigma_u^2/(\sigma_u^2+\sigma_v^2)$		-	-	$\gamma = \sigma_u^2/(\sigma_u^2+\sigma_v^2)$	0.95	19.68***
Log likelihood		-284.36			-152.37	
Inefficiency Function						
Constant		-	-	δ_0	-8.707	-0.87
Age		-	-	δ_1	-0.004	-0.172
Education		-	-	δ_2	0.172	0.945
Family size		-	-	δ_3	-0.299	-0.877
Off-farm income		-	-	δ_4	6.800	1.062
Extension visits		-	-	δ_5	-0.011	-0.250
Region		-	-	δ_6	2.156	1.160
Farm size		-	-	δ_7	0.0009	0.914
Distance to market		-	-	δ_8	0.404	1.073
Number of selected observations		174			174	

participants and non-participants were Taka 22,462 (SD 10,795) and 39,636 (SD 19,663) respectively. The table shows that only 16% of the microfinance participants had incurred profit-loss of Taka 30000 per hectare and above, whereas 61% of the non-participants had estimated loss in profit of Taka 30000 per hectare and above. From the results it is evident that microfinance participants incurred significantly less profit-loss per hectare and operate at significantly higher level of profit efficiency. However, there is no significant difference in terms of earning actual profit per hectare between the two groups.

The results suggest that clear opportunities exist to increase the profit efficiency of rice farms for both groups by eliminating their technical and allocative inefficiencies. The improvement potential with respect to the profit-loss was even greater for the non-participants than for the microfinance participants.

Determinants of Profit Inefficiency: The results indicated that farmers in both groups exhibited a wide range of profit inefficiency. It is, therefore, important to examine more in detail whether farm specific socio-economic factors influence profit inefficiency in rice farming. The lower part of Table 2 presents the determinants of inefficiency for the group of microfinance participants only based on the conventional stochastic profit frontier (see table 6 for the estimation of non-participants). The results show that five variables out of the eight variables are significantly different from zero with expected signs. The findings suggest that age, as a proxy of farming experience, extension visits and the location (north-western region) significantly increase profit efficiency. On the other hand, larger off-farm income share and farm size significantly reduce the profit efficiency. The statistically significant coefficient of age, as proxy of farming experience, implies that an increasing number of years in rice farming led to the acquisition of better managerial skills over the years and helped the farms to improve profit efficiency. This result corroborates with the findings of previous studies [23, 39]. The results show that education as measured in years of schooling had no significant impact on profit efficiency. A conceivable argument could be that five or more years of formal education are required before increases in efficiency could be observed (Table 1). Similar results have been documented in the previous results of technical and profit efficiency analysis in Bangladesh [14, 23].

The positive and highly significant coefficient of the off-farm income indicated that farmers who had greater off-farm income tended to have higher levels of inefficiency. Ali and Flinn [20] reported similar results. Having greater off-farm income entails the reallocation of time not spent on farming activities. Such "lost farm activities" may have involved the gathering of technical information and also the adoption of new technologies, which are known to be crucial for farm production efficiency [40]. It also deprives the farm of valuable time to perform the farming activities in a timely manner. Extension visits significantly reduced inefficiency in our study. This indicates that increasing access to extension services for rice farmers would be beneficial to reduce the farm inefficiencies through the dissemination of new information and implementation of new technologies. Our results show that 73% of the surveyed farms had access to extension visits. Moreover, the credit borrowers had the added advantage of acquiring information and receiving on farm training from their respective credit providers. These augmented services and extension visits had a significant impact on farm profit efficiency in our study. Our findings are consistent with those of previous studies [23, 28, 41]. The policy implication of this finding is that a realistic package that will increase the number of farmers reached by the extension contacts as well as training of the extension personnel of all categorise should be harnessed as a vital step towards sustainable agricultural production in Bangladesh. The significant positive coefficient of farm size on profit inefficiency indicates that large farms tended to be more profit inefficient compared to the smaller farms. This result is in line with previous studies [30]. The significant region dummy implied that farmers in the north-western region are less efficient, even when other factors confounding efficiency were considered. This finding reinforces the argument that concentrating on specific regional problems encountered in rice growing is a vital policy instrument that should be addressed in formulating more focused agricultural policy in Bangladesh. The coefficients on the family size and distance of home to market, however, are not significantly different from zero.

CONCLUSION

This study applied a sample selection framework in stochastic profit frontier models to analyze the contribution of microfinance on profit efficiency and profit-loss of rice farms in north-central and north-western regions of Bangladesh using survey data obtained over 2008-2009 growing seasons. The model diagnostic indicated that serious selection bias exists that justifies the use of sample selection framework. Results of the profit efficiency indicated that, after correcting for selectivity bias, microfinance participants exhibited significantly higher profit efficiency and incurred significantly less profit-loss per hectare than the non-participants. The mean levels of profit efficiency of microfinance participants and non-participants are estimated at 68% and 52% respectively and thereby suggesting that substantial amounts of the potential profits are lost due to technical, allocative and scale inefficiency. Thus, this purely observational study has documented a positive relationship between access to microfinance and farms' profit efficiency.

The results of inefficiency analysis suggested that farmers with more experience in farming, located in north-central region and having more interactions with extension agents tended to be more profit efficient. On the other hand, increasing off-farm income share and farm size tended to lower profit efficiency. Given the variation in actual profit, profit efficiency and profit-loss, there appears to be substantial potential for both groups to improve profit efficiency and to minimize profit-losses with greater scope especially for the non-borrowers.

For policy implications, greater government support to strengthening the extension services as well as more focused concentration on reducing the shortfalls of north-western region are recommended as priority objectives to increase profit efficiency and to reduce profit-loss. The findings of the relationship between microfinance and profit efficiency suggest that getting more access to agricultural microfinance for farmers will improve production, profit efficiency and reduce the profit-losses. Consequently, streamlining the microfinance to small scale farmers by all tiers of the government would be a vital factor to increasing farm performance.

However, this r equires a multi-disciplinary approach that needs to be addressed more rigorously by the government agricultural policy makers in collaboration with NGOs and the donor agencies.

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