

Technical, Economic and Allocative Efficiency of Microfinance Borrowers and Non-Borrowers: Evidence from Peasant Farming in Bangladesh

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Abstract

This paper empirically examines the technical, economic and allocative efficiency of agricultural microfinance borrowers and non-borrowers in rice farming in Bangladesh using Data Envelopment Analysis (DEA) of survey data obtained in 2009. Inefficiency effects are modeled as a function of farm-specific and institutional variables. The mean technical, allocative, and economic efficiencies are found to be 72%, 66%, and 47 % respectively in the pooled sample under variable returns to scale specification. This indicates the existence of substantial gains in output and/or decreases in cost in the study areas. Results reveal that after effectively correcting for sample selection bias, land fragmentation, family size, household wealth, on farm-training and off-farm income share are the main determinants of inefficiency. Efficiency scores between microfinance borrowers and non-borrowers are significantly different which are also conformed by the non-discretionary DEA model. This study also revealed that excess costs owing to inefficiencies was 53% and concludes that main challenge facing the rice farmers in Bangladesh is to develop their cost minimizing skills. Some indicative policy guidelines to improve efficiencies are also suggested.

Keywords: Technical, Economic and Allocative efficiency, Selection Bias, Microfinance, Non-Discretionary DEA model, Bangladesh.

1. Introduction

Agriculture is the most important sector in the economy of Bangladesh and the economic prosperity of the country depends upon sustained growth in agricultural production and productivity. It accounts for 21% of the gross domestic product (GDP) and 50% of overall employment (Bangladesh Agricultural Census, 2008). It continues to show strong performance particularly in the food grain sub-sector. The dominant food crop of Bangladesh is rice which accounts for 94% of the cereals consumed, supplies 68% of the protein in the national diet, accounts for approximately 78% of the value of agricultural

output, and amounts to 30% of consumer spending (Ahmed and Haggblade, 2000). It also accounts for 94% of the total crops produced (Bangladesh Economic Review, 2009), and 77% of the cropped area (BBS, 2006). The wide spread use of high yielding varieties of seed, the successful research effort by Bangladesh Rice Research Institute (BRRI, 2000), and the use of fertilizer through easing the imports of this item have increased crop yields in the 1990s. Some researchers contend that with its abundant water resources and low crop yields, Bangladesh has relatively higher potential for expanding food production than many other developing countries by maintaining the momentum of the green revolution (Brown and Kane, 1994). The average rice yield in Bangladesh is 2.74 tonnes/ha (BBS, 2008) which is much lower compared to those of other Asian countries. Thus the potential gain from closing the yield gap in Bangladesh is higher than for China, Korea, Indonesia, Myanmar, Nepal and Vietnam (Pingali et al., 1997).

Several recent studies on the technical efficiency (TE) and economic efficiency (EE) of crop production for rice and wheat indicated the existence of a 'yield gap'. This 'gap' refers to the difference in productivity between 'best practice farms' and other farms that operate with comparable available resources under similar circumstances (Villano, 2005). The presence of shortfalls in efficiency indicates that output can be increased with given inputs and existing technologies. If this is the case, then empirical estimations of efficiency are important to determine the gain that could be obtained by improving the performance in production with existing technology. It also helps to find out whether the yield variability is due to random influences beyond the control of the farmers or to the factors under the control of the farms.

To date there have been very few studies undertaken in Bangladesh that measured TE, AE and EE of rice producers. Wadud and White (2000) used both DEA and Stochastic Frontier Approach (SFA) to examine the TE of a sample of 150 farmers in two villages. They obtained high level of TE (79%) and scale efficiency (SE) (92%), which were partly explained by environmental degradation and irrigation infrastructure. Coelli, Rahman, and Thirtle (2002) used DEA to determine TE, allocative efficiency (AE), cost and SE for the modern Aman and modern Boro rice varieties from a sample of 406 households. For Aman rice they reported TE of 66%, whilst for Boro rice TE was 69%. SE for the above two varieties were 93.3% and 94.9% respectively. Khan, Huda, and Alam (2010) examined how farmers' age, education and experience influenced TE of boro and aman rice producers using Cobb-Douglas production frontier and found that education was positively related to TE. However, none of these studies focused on the potential contributions of agricultural microfinance to enhancing the productivity and efficiency of rice farmers in Bangladesh.

Given this back drop, the present study assesses the effects of the farmer's access to microfinance on TE, AE and EE by applying DEA models and a sample selection model. This study also attempts to test the hypothesis that access to agricultural microfinance affects TE, AE and EE of the farm households in Bangladesh. We applied a non-discretionary DEA model to assess the impact of financial factor (microfinance) on the rice production performance and efficiency. The aim of this model is to investigate if farms are constrained by credits, how does their performance compare to their counterparts? This model is an extension to the efficiency studies in that it compares farms' performance in the presence of environmental inputs¹. An improved understanding of these relationships can help the farmers to allocate scarce resources more efficiently and may assist policy makers to design and formulate agricultural policy to increase agricultural production in Bangladesh.

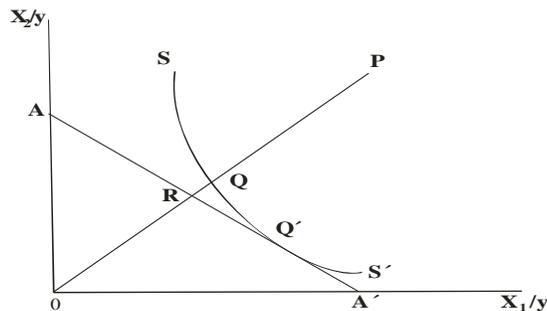
The rest of the paper is organized as follows. Section 2 outlines the theoretical framework. Section 3 provides the empirical models followed by data sources and the details of variable construction in section 4. Empirical results and discussions are presented in section 5. Summary of the findings and policy guidelines are suggested in the final section.

¹ An environmental input is a factor of production that cannot be adjusted instantly by the operators and is assumed to be fixed in the short term. We consider the amount of microfinance given to the borrowers is fixed and is beyond the control of the borrowers.

2. Analytical Framework

Farrell's (1957) seminal article on efficiency measurement led to the development of several approaches to efficiency and productivity analysis. Among these, SFA (Aigner et al., 1977; Meeusen and van den Broeck, 1977) and DEA (Charnes et al., 1978) are two revolutionary contributions. The main difference between the two methods is that, since SFA is parametric, it takes into account both the inefficiencies and white noise, while the DEA is nonparametric and it attributes all deviations from the frontier to inefficiency. Coelli (1995) provides a comprehensive overview of the strengths and weakness of SFA and DEA frontiers. The breakthrough paper of Charnes-Cooper and Rhodes-CCR (1978) led to the development of DEA approach, a new methodology widely used to measure the relative efficiency of decision making units (DMUs) by providing an estimate for the projection of inefficient DMUs onto an 'efficiency frontier'. These projections may involve input contractions or output expansion, or both. From input-orientation, the efficiency of these DMUs are calculated as the radial reduction² in inputs to the inputs levels of the best performing DMUs to produce the same level of output. The DEA method can be applied using either an output based or an input-based approach depending on whether these approaches use input distance function or output distance function. These two measures are not equal unless we assume constant returns to scale (CRS) (Färe et al., 1994). Under the input oriented measure, knowledge of the unit isoquant makes it possible to describe the TE of the farms in the sample. From the isocost line we can measure the AE and EE of a farm. If a single output (y) and two inputs (x_1, x_2) are assumed, the input-oriented DEA can be portrayed in the following figure 1. The iso-quant of fully efficient farms is represented by SS' in the figure given below. If a given farm uses input quantities of x_1 and x_2 to produce one unit of output y , defined by the point P , then the technical inefficiency of the farm could be represented by the distance QP , which is the amount by which all inputs could be proportionately (i.e., radial reduction) reduced without a reduction in output.

Figure 1: Input oriented measures of TE and AE for one output and two inputs. *Source:* Coelli et al., 1998, p. 135.



The TE of a farm is most commonly measured by the ratio OQ/OP , which is equal to $1-QP/OP$. A value of 1 indicates that the farm is fully technically efficient. If the input price ratio represented by the slope of the isocost line AA' is known, then for the farm operating at point P , the AE would be the ratio OR/OQ . The distance RQ represents the reduction in production cost if the farm operate at both the technically and allocatively efficient point at Q' , instead of at the technically efficient, but allocatively inefficient, point Q . The EE is just the product of TE and AE and is defined by the ratio OR/OP , where the distance RP represents the possible reduction in cost if the farm operates in an economically efficient way.

² Radial reduction aims at obtaining the maximum rate of reduction with same proportion, e.g., a radial contraction in the two inputs (for two inputs case) that can produce the current output.

3. Model Specification

3.1. Input-Oriented DEA Approach

Following Farrell (1957), the production possibility set for a particular DMU is represented by enveloping the observations as tightly as possible by a piecewise linear outer boundary:

$$T = \left\{ (x, y) : \sum_{j=1}^J \lambda_j x_{nj} \leq x_n (n=1, \dots, N), \sum_{j=1}^J \lambda_j y_{mj} \leq y_m (m=1, \dots, M), \sum_{j=1}^J \lambda_j = 1 (j=1, \dots, J) \right\} \quad (1)$$

There are J observations and the nonnegative weights, λ_j , determines the reference point on the frontier. The constraint, $\sum_j \lambda_j = 1$, implies that the sum of lambdas equals one and ensures the assumption of variable returns to scale (VRS). M defines the number of outputs, N defines the number of inputs and T defines the production possibility set. For the i^{th} farm, out of J farms, the input-oriented TE under CRS is obtained by solving the following linear programming (LP) problem:

$$TE_i = \underset{\theta_i, \lambda}{\text{Min}} \quad \theta_i^{CRS}$$

Subject to:

$$\sum_{j=1}^J \lambda_j y_{mj} - y_{mi} \geq 0, m = 1, \dots, M$$

$$\theta_i x_{ni} - \sum_{j=1}^J \lambda_j x_{nj} \geq 0, n = 1, \dots, N \quad (2)$$

$$\lambda_j \geq 0, j = 1, \dots, J$$

$$\theta_i \in (0, 1]$$

Following Førsund and Hjalmarsson (2004), the unit index, i , is suppressed on the λ weights and the same symbols are used for the λ weights in equations (1) and (2) for notational ease. Here x and y are the input and output vector respectively, θ_i^{CRS} is a scalar that defines the TE of farm i under CRS. It satisfies $\theta \leq 1$, with a score 1 indicating that the farm is producing on the production frontier and hence is technically efficient, according to the definition provided by Farrell (1957). The CCR (Charnes-Cooper-Rhodes, 1978) CRS linear programming model can be easily modified to VRS by adding the convexity constraint: $\sum_j \lambda_j = 1$, where $\lambda_j \geq 0, j = 1, \dots, J$, to equation (2) (Banker et al., 1984). This approach forms a convex hull of intersecting planes which envelopes the data points more closely than under the CRS. The convexity constraint $\sum_j \lambda_j = 1$ ensures that the inefficient farm is ‘benched mark’ only against farms of similar size. The EE and AE are obtained through solving the following cost minimization LP under the VRS input oriented DEA model:

min

$$\lambda, x_i^* w_i^* x_i^*$$

Subject to

$$\sum_{j=1}^J \lambda_j y_{mj} - y_{mi} \geq 0, m = 1, \dots, M$$

$$x_{ni}^* - \sum_{j=1}^J \lambda_j x_{nj} \geq 0, n = 1, \dots, N \quad (3)$$

$$\sum_j^J \lambda_j = 1$$

$$\lambda_j \geq 0, j=1, \dots, J$$

$$\theta_i \in (0,1]$$

where w_i is a vector of input prices for the i^{th} farm and x_{ni}^* (which is calculated by LP) is the cost minimizing vector of input quantities for the i^{th} farm, given the input prices w_i and the output levels y_i . The total cost efficiency (CE) or EE of the i^{th} farm is calculated by comparing the minimum cost of the farm to its actual cost:

$$EE_i = \frac{w_i' x_{ni}^*}{w_i' x_i} \tag{4}$$

The AE is calculated residually by following the definition of Farrell (1957)

$$AE_i = \frac{EE_i}{TE_i} \tag{5}$$

Given that the production technology is of VRS type, SE measure can be obtained by conducting both a CRS and VRS DEA and can be represented by using the following formulae (Coelli et al., 2005):

$$SE_i = \frac{TE_{CRS}}{TE_{VRS}} \tag{6}$$

In general, $0 \leq SE \leq 1$, with $SE = 1$ representing CRS (optimal scale), $SE < 1$ implies increasing returns to scale (IRS) (sub-optimal scale) and $S > 1$ representing decreasing returns to scale (DRS) (super- optimal scale). A farm will operate at its optimal scale when $TE_{CRS} = TE_{VRS}$, where equality means that the farm is operating under CRS (Coelli et al., 2005).

3.2. Non-Discretionary DEA Model with Microfinance

This paper employs a non-discretionary DEA model where the efficiency scores are intended to reflect not only the difference between the discretionary factors but also differences in external non-discretionary conditions. The motivation of non-discretionary DEA models is to ensure fair comparison in performance assessment such that DMUs facing unfavorable conditions that they cannot influence are not penalized for producing less outputs or consuming more inputs than their peers. In the present study we apply a non-discretionary DEA model to investigate the effect of strictly monitored and administered microfinance program on farms’ production and cost efficiency. We define the term microfinance as a non-discretionary variable since the microfinance borrowers cannot influence the amounts loaned which is solely determined by the credit evaluators. So, this external environmental variable (Coelli et al., 1998, p.169) cannot be adjusted by the farmer in short period and to measure its influence on farm efficiency, we incorporate this fixed variable directly into the following LP formulation:

$$TE_i = \underset{\theta_i, \lambda}{Min} \theta_i^{CRS}$$

Subject to:

$$\sum_{j=1}^J \lambda_j y_{mj} - y_{mi} \geq 0, 1, \dots, M$$

$$\theta_i x_{ni} - \sum_{j=1}^J \lambda_j x_{nj} \geq 0, n = 1, \dots, N$$

$$h_{ni} - \sum_{j=1}^J \lambda_j h_{nj} \geq 0 \tag{7}$$

$$\sum_j^J \lambda_j = 1$$

$$\lambda_j \geq 0, j=1, \dots, J$$

$$\theta_i \in (0,1]$$

In the above equations, $\sum_{j=1}^J \lambda_j h_{nj}$ represents the environment of the theoretical farm and the i^{th}

farm would be compared with this theoretical farm that has similar level of debt (from sources other than the agricultural microfinance loan) as that of the i^{th} farm. This formulation ensures that i^{th} farm is only compared to a (theoretical) frontier farm which has the same environment (Coelli et al., 1998, p.170). In this non-discretionary model, efficiencies are calculated from the same number inputs (discretionary) and outputs like that of CRS DEA (equation 2) but the frontier changes depending upon the DMU being assessed (since for each DMU the peers are only those DMUs representing equal environmental condition) (Coelli et al., 1998, p.170; Ruggiero, 1996). The EE and AE are obtained through solving following cost minimization LP problem under VRS DEA:

$$\min_{\lambda, x^*, w^*, v^*}$$

$$\sum_{j=1}^J \lambda_j y_{mj} - y_{mi} \geq 0, m = 1, \dots, M$$

$$x_{ni}^* - \sum_{j=1}^J \lambda_j x_{nj} \geq 0, n = 1, \dots, N \tag{8}$$

$$h_{ni} - \sum_{j=1}^J \lambda_j h_{nj} \geq 0$$

$$\sum_j^J \lambda_j = 1$$

$$\lambda_j \geq 0, j=1, \dots, J$$

$$\theta_i \in (0,1]$$

3.3. Tobit Model with Sample Selection

The data we use in the present study were collected after some underlying selection process already took place that is farm households already opted to behave one way or the other. This means that some households already decided to participate in the microfinance program while others did not. Thus the underlying selection process is postulated on the presence or absence of participating in microfinance program. Following Greene (2006) we apply the following internally consistent method of incorporating ‘sample selection’ into a model. The first model is household’s participation to microfinance program (equation 9). The second model (equation 10) relates to the factors explaining efficiency (TE, AE and EE) of rice producers in which the household’s participation to microfinance (selection variable) which does not appear in the index function (βx) of equation (10) but affects the conditional mean function through its effect on the inverse mills ratio (‘selection variable’). We specify the Tobit model with selectivity as follows:

$$z^* = \alpha'w + u, \text{ [probit model based on } z^* = \alpha'w + u, \text{]} \tag{9}$$

$$z = 1 \text{ if } z^* > 0$$

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

$$y^* = \beta'x + \varepsilon, \text{ [Tobit model censored from below at the value of 0]} \tag{10}$$

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

$$\varepsilon, u \sim N[0, 0, \sigma_\varepsilon^2, \sigma_u^2, \rho].$$

$$\text{Corr}[\varepsilon, u] = \rho$$

$[y, x]$ observed only when $z = 1$

where, z is a probit selection equation, y is the efficiency score (specified only for microfinance borrowers), w represents farm household characteristics that determine participation in the agricultural microfinance program and x is a matrix of households' socioeconomic and demographic characteristics that are assumed to influence efficiency. Note that in the estimated model the dependent variable (y) is efficiency score and the distribution of estimated efficiencies is censored at 0 from below. The variable z^* is such that an observation is drawn from the model only when z^* crosses some threshold, the standard deviations are σ_ε and σ_u , and the covariance is $\rho\sigma_\varepsilon\sigma_u$. The disturbance terms (u, ε) have zero mean, bivariate normal distribution with a unit variance and $\rho = \text{Cor}(u, \varepsilon)$. Greene (2000) and Wooldridge (2002), however, noted that if $\rho \neq 0$, then u, ε are correlated and the estimation of equation (10) through OLS leads to biased estimates of β . The procedure for the estimating the sample selectivity in LIMDEP (version 7.0) is as follows: (1) Fit the probit model for the sample selection equation (equation 9) and hold them for the second step. (2) Using the probit results in step (1) fit the sample selection model.

4. Data and Descriptive Statistics

4.1. Data Sources

This study is based on the cross-sectional farm level data collected from six districts in the north-central and north-west regions in Bangladesh during 2008-09 growing seasons. These regions were selected due to their high levels of poverty and good agricultural potential as well as for the presence of IFAD funded agricultural microfinance project. From each district, two villages are chosen at random. Microfinance borrowers' data were collected with the help of microfinance institutions (MFIs) clients' lists. The samples of borrowers are randomly selected without replacement from the list of borrowers available from the programs' local office of each program village surveyed. Non-borrowers are selected based on similar land holdings and socio-economic background to provide a control group for comparison with borrowers. A total of 360 farmers were interviewed of which 180 farmers were the participants of microfinance, while the remaining 180 farmers were non-participants of microfinance. However, in applying DEA models, we used 355 farms since there were zero usages of some inputs by five farms.

4.2. Variable Construction

Rice output prices were gathered from individual farms. All rice produced on the sample farms were aggregated into one output value (Taka³) which was the dependent variable. Land represented the total amount of land (own-cultivated land, sharecropping land, and rented/leased land) used for rice production and price (p_1) of land represented annual rent per decimal⁴ of land. Labor included both family (imputed for hired labor) and hired labor utilized for pre and post planting operations and harvesting excluding threshing and price (p_2) of labor included the price of hired labor per day. Seeds included all seeds used in rice production and price included the average price (p_3) of seed (Taka/kg) used for rice cultivation. Fertilizers included all organic and inorganic fertilizers used and are measured in (kg). The price (p_4) of fertilizer was the weighted average of all fertilizers purchased for rice cultivation. Irrigation covered the total areas of land irrigated for rice cultivation and price (p_5) included the price of irrigation per decimal land. Tilling included the total land tilled with tractor

³ USD 1= Taka 69. 80 ; Euro 1= Taka 89.60 (as of October 30, 2010).

⁴ Traditionally farmers in the study areas use decimal to measure the land. 247 decimals = 1 hectare

and/or bullocks and the price of tilling (p_6) included the tilling cost per decimal land. Other costs included pesticide and seed bed preparation, and price was considered to be uniform for all farms and it was denoted by (p_7).

Table 1: Descriptive statistics of the data

Variables	Microfinance borrowers (N=179)		Non-borrowers of microfinance (N= 176)		t-ratio
	Mean value	Std. Dev.	Mean value	Std. Dev.	
Output Value (Taka)	85911.47	86144.57	91766.27	111391.3	-0.55
Land (Decimal)	272.62	307.76	345.11	486.40	-1.67*
Labor (days)	194.89	169.73	203.43	179.20	-0.46
Seeds (kg)	56.26	64.89	81.26	257.77	-1.25
Fertilizers (kg)	448.35	494.55	508.97	771.92	-0.68
Irrigated land (Decimal)	357.97	483.66	359.08	517.48	-0.02
Tilling land (Decimal)	433.04	470.76	482.29	641.60	-0.82
Other variable costs (Taka)	2748.63	2985.48	3183.80	4397.68	-1.09
Land rent (Taka/decimal)	633.76	428.97	719.24	445.39	-1.84*
Labor wage (Taka/day)	150.72	46.24	150.40	48.08	0.06
Seed price (Taka/kg)	57.99	54.46	64.82	56.30	-1.16
Fertilizer price (Taka/kg)	22.84	8.27	22.88	8.64	-0.04
Irrigation price (Taka/decimal)	24.50	21.11	24.96	19.21	-0.21
Tilling price (Taka/decimal)	14.79	12.10	17.22	19.21	-1.42
<i>Farm-specific variables</i>					
Age of farmer (Years)	41.94	12.59	43.53	13.96	-1.13
Education of household head (Years)	4.98	4.58	5.00	4.67	-0.04
Family size	4.60	1.79	4.71	1.81	-0.57
Extension visits (No/year.)	6.18	7.01	6.07	7.60	-0.18
Non-agricultural income share (%)	35.64	27.86	39.82	28.71	-1.39
Experience (Years)	21.37	11.96	24.83	14.22	-2.47**
Numbers of rice plots (No.)	4.36	2.19	3.73	2.12	2.75***
Wealth (Taka)	252265.4	293269.4	299784.3	367204.3	-1.35
Expenditure (Taka/month)	6534.27	4424.86	6774.46	4403.84	-0.51
Distance of home to market (Km.)	1.07	1.08	1.09	0.78	-0.20
On-farm training (%)	31.27	46.42	27.27	44.66	0.82

Note: ***, **, and * indicate significant at 1% ($P < 0.01$), 5% ($P < 0.05$), and 10% ($P < 0.10$) level.

Table 1 shows the descriptive statistics of the output and input used in the DEA estimation and other, relevant to the inefficiency effect model, variables. It is evident from the table that there is no statistically significant difference between the microfinance borrowers and non-borrowers in terms of output value and the levels of input use except for cultivated land and annual land rent. In terms of physical and socio-economic characteristics both groups seem to be homogenous and the averages of different household characteristics are not significantly different between the two groups except for farming experience and number of plots operated. With regard to wealth, there is a marked difference between the two groups. The figures show that non-borrowers of microfinance are wealthier (Taka 299748) than the borrowers (Taka 252265) although the difference is not statistically significant.

5. Results and Discussions

5.1. Efficiency Scores in the Pooled Sample

The input-oriented DEA models are calculated using equations (2), (3), and (6) by the computer program DEAP (Coelli, 1996) for the same number of inputs, outputs and farm households and the results of pooled sample are presented in Table 2. The last four rows of the same table show the number of farms that are operating at CRS, DRS, IRS and with SE.

Table 2: Efficiency Indices for the Pooled Sample of 355 Paddy Farms

Efficiency Scores (%)	DEA CRS				DEA VRS			
	Mean	Min	Max	SD	Mean	Min	Max	SD
TE	63.4	20.3	100	19.24	71.9	29.3	100	19.29
AE	61.9	13.8	100	17.38	66	14.8	100	16.27
EE	38.7	7.9	100	19.92	46.8	10	100	16.35
CRS (%)	10.99							
DRS (%)	16.33							
IRS (%)	72.68							
SE (%)	88							

In the pooled sample the mean scores of TE, AE, and EE are 63.4%, 61.9% and 38.7 % for CRS DEA model and those are 71.9%, 66%, and 46.8 % for VRS DEA model. The results of both models, especially with CRS assumption, show that there are substantial inefficiencies in the agricultural production activities in the sampled areas during the survey. This indicates that there is substantial scope to reduce production costs and hence obtain output gain through improving efficiency. The low AE and EE scores indicate that if the farmers operate at the optimal efficiency level, they can reduce, on average, the production cost by 53.2% while producing the same level of output under VRS assumption.

5.2. Efficiency Scores in the Pooled Sample for Microfinance Borrowers and Non-Borrowers

Table 3 presents efficiency distribution of microfinance borrowers and non-borrowers. The efficiency indices of Table 3 are based on the pooled sample taken from Table 2. The mean values of TE, AE, and EE are 64.5%, 63.7% and 40.5 % for CRS DEA model for the microfinance borrowers and those are 62.2%, 59.9%, and 36.9 % for CRS DEA model for the non-borrowers of microfinance. Under CRS DEA model, the microfinance borrowers thus exhibit 2.3%, 3.8% and 3.6% higher TE, AE and EE scores. Under VRS DEA model the corresponding efficiency scores are higher by 1.3%, 2.6%, and 2.48 % respectively. The average TE scores (under CRS DEA) of both groups thus indicate that farmers are producing 64.5% and 62.2% of the potential output (e.g., the frontier production). In terms of TE, under CRS DEA model, only 14 microfinance borrowers are found to be fully efficient, whereas, 16 non-borrowers are found to be fully efficient. Estimates of AE indicates that, on average, participants of microfinance could reduce the cost by 36.3% under CRS DEA (32.7% under VRS DEA model) by taking into account the input prices while selecting the input quantities. On the other hand, the non-participants could bring down cost by 41.1% under CRS DEA (35.3% under VRS DEA model) by doing the same. The combined effect of TE and AE are reflected through EE and show that, under CRS DEA model, both groups can reduce the costs by 59.5% and 63.1% respectively. On the other hand, under VRS DEA model, they can bring down the costs of production by 51.92% and 54.4% respectively.

Table 3: Distribution of Efficiency Indices of Microfinance Borrowers and Non-Borrowers

Efficiency Interval	Microfinance Borrowers						Non-Borrowers of Microfinance					
	DEA CRS			DEA VRS			DEA CRS			DEA VRS		
	TE	AE	EE	TE	AE	EE	TE	AE	EE	TE	AE	EE
≥ 0.90 ≤ 1.00	0	0	0	0	0	0	0	0	2	0	0	1
≥ 0.80 ≤ 0.90	0	1	8	0	1	1	0	0	17	0	0	8
≥ 0.70 ≤ 0.80	1	1	34	0	1	16	3	9	45	1	5	19
≥ 0.60 ≤ 0.70	11	7	47	2	5	32	21	13	46	9	11	44
≥ 0.50 ≤ 0.60	30	20	57	21	13	65	31	29	34	23	25	46
≥ 0.40 ≤ 0.50	40	39	15	21	37	36	35	33	18	24	30	31
≥ 0.30 ≤ 0.40	37	44	11	44	34	14	30	34	10	32	33	11
≥ 0.20 ≤ 0.30	22	48	5	35	53	7	19	41	3	24	32	7
≥ 0.10 ≤ 0.20	13	17	2	15	28	4	11	16	0	19	32	3
≥ 0 ≤ 0.10	25	2	0	41	7	4	26	1	1	44	8	6

Total	179	179	179	179	179	179	176	176	176	176	176	176
Mean	64.5	63.7	40.5	72.5	67.31	48.08	62.2	59.59	36.9	71.2	64.7	45.6
Std.	18.57	16.38	19.06	17.88	16.59	19.03	20.24	18.23	20.65	19.78	19.36	17.68
Min.	20.3	13.8	12	35.3	14.8	14.8	24.1	23	7.9	29.3	22.9	10
Max.	100	92	84.7	100	97.6	97.2	100	100	100	100	100	100
CRS (%)	11.17						10.8					
DRS (%)	16.2						16.48					
IRS (%)	72.63						72.72					
SE (%)	89						87					

As shown in table 3, the lower efficiency levels indicate that both groups are rather homogenous, meaning that there is greater scope for efficiency improvements by increasing output with available inputs and given technology. Thus, under CRS DEA model, if average farms in the sample of microfinance borrowers could reach to the EE level of its most efficient counterpart by operating at optimal scale and on the minimum cost frontier, they could reduce cost of production by 52.18% (e.g., 1- [40.5/84.7]). For the most economically inefficient farmer in this group could reduce the cost by 85.83% (e.g., 1- [12/84.7]) while producing the same level of output. For the non-borrowers of microfinance, average farmers could bring down the cost by 63.1% (e.g., 1-[36.9/100]). It is thus evident from the results of the DEA models that for both groups the EE could be improved substantially. From the results in Table 3, it is evident that AE is the dominant inefficiency component in overall economic inefficiency compared to technical inefficiency. This finding shows that the main problem of both groups are their inability to allocate inputs in the most cost minimizing way rather than using the inputs in a technically efficient way.

Solving the equation (6) we obtained the mean SE ($SE = TE_{CRS} \div TE_{VRS}$) of both the borrowers and non-borrowers of microfinance. Results reveal that in both groups the mean SE were 89% and 87% respectively and thereby suggesting that SE is close to unity for each DMU. These results imply that scale inefficiency is not present among the farms and since the farms are very small, scale economies may only be realized by larger farms. This finding conforms to the result of previous study (Coelli et al., 2002). It also indicates that if the average farms were operating at optimal scale, they could improve the efficiency by 11% and 13% respectively. Finally, to substantiate the nature of scale inefficiencies, the analysis further disaggregated into those farms that exhibited IRS and DRS in both groups. Information as to whether farms are operating at IRS or DRS can provide useful information to indicating the potential redistribution of farm resources to maximize productivity. In brief, the results are fairly distributed and show that farms are almost similar in terms of size in both groups.

5.3. Efficiency Scores in the Non-discretionary DEA Model

This section describes the results obtained in the efficiency assessment of two groups by taking into account the effect of external non-discretionary factor. However, this model was modified in the sense that the microfinance borrowers were compared only to those farms with same level of debt. The modified model considered 179 microfinance borrowers as before and 158 non-borrowers of microfinance that had same level of debt⁵.

⁵ To make the debt level comparable, we consider 158 non-borrowers who had average debts (from sources other than the agricultural microfinance loan) equal to the average debt level of microfinance borrowers.

Table 4: Impact of the Non-Discretionary Variable (Microfinance) on Efficiency

	DEA efficiency scores of non-borrowers of microfinance						DEA efficiency scores of the microfinance borrowers					
	DEA CRS			DEA VRS			DEA CRS			DEA VRS		
	TE	AE	EE	TE	AE	EE	TE	AE	EE	TE	AE	EE
Mean	68	55	37	77	62	47	71	70	50	80	69	55
Min	27.6	22.8	7.9	36	23	10	24.8	15.6	14.9	38.7	15.8	15.8
Max	100	100	100	100	100	100	100	100	100	100	100	100
SD	21.21	15.32	15.34	20.63	17.51	18.75	17.65	15.8	16.23	17.06	15.5	17.7
CRS(%)	17.72						14.53					
DRS(%)	14.56						30.17					
IRS (%)	67.72						55.3					
SE (%)	89						88					
Total	158	158	158	158	158	158	179	179	179	179	179	179

Table 4 reflects the differences between efficiency scores for the two groups calculated from the same discretionary inputs (equation 2) where the criteria used for peer selection was having the access to external non-discretionary input (access to microfinance). The table shows that microfinance borrowers, under CRS assumption, had 3%, 15%, and 13% higher TE, AE, and EE compared to their peers. These indices are higher by 3%, 7%, and 8% respectively under VRS assumption. It is thus evident from the efficiency scores of non-discretionary DEA models is that under the strict control and supervision of microfinance, the microfinance borrowers displayed significantly higher efficiency compared to their non-borrowing counterparts who had similar debt from informal and/or from government’s subsidized loans provided by mainstream commercial banks. Note that the benchmarks identified by the non-discretionary model has a similar environment (e.g., similar level of debt) for both groups and the empirical evidence suggests that the efficiency of both groups can be further increased with greater increase potential for the non-borrowers.

5.4. Test of Hypotheses

Results of the statistical tests are shown in Table 5. The *t*-tests values in the pooled sample show significant differences in the means for AE, and EE under both CRS DEA and VRS DEA models. For mean AE and EE indices, the *t*-test values of 2.08, 1.72 (under CRS assumption), with degrees of freedom of 353, exceed the critical value of 1.96 at 5% and 1.65 at 10% significant level. Thus the null hypotheses were rejected indicating that the differences between means (for AE and EE) are more than zeros. However, there is no statistically significant difference between the two groups in terms of average TE. For AE, EE we also get the similar results (Table 5) under non-discretionary DEA model and we conclude that under both comparisons mean efficiency indices are significantly different. It indicates that the microfinance participants have significantly higher AE and EE compared to their peers as the mean difference test statistics⁶ reported in Table 5 show.

Table 5: Statistical Test Statistics for Differences in Efficiency Scores from DEA CRS and DEA VRS

	Pooled Sample						Non-discretionary DEA model					
	DEA CRS			DEA VRS			DEA CRS			DEA VRS		
	TE	AE	EE	TE	AE	EE	TE	AE	EE	TE	AE	EE
t-ratio	1.12	2.08**	1.72*	0.65	1.66*	1.72*	1.41	8.83***	7.55***	1.45	3.86***	4.01***

Notes: ***, **, and * indicate significant at 1% (P<0.01), 5% (P<0.05), and 10% (0.10) level, respectively.

⁶ The reported t-test values were derived as $t = \frac{\bar{x}_1 - \bar{x}_2}{s} \sqrt{\frac{n_1 n_2}{n_1 + n_2}}$, where $s = \sqrt{\frac{(n_1 - 1)s_1^2 + (n_2 - 1)s_2^2}{n_1 + n_2 - 2}}$, and \bar{x}_1 and \bar{x}_2 are sample means of the microfinance borrowers and non-borrowers respectively.

Thus, it can be concluded that microfinance participants displayed significantly higher AE and EE that demonstrate the influence of microfinance on efficiency.

5.5. Results of Probit Model for Participating in Microfinance Program

The results of the probit selection equation (Table 6) show the relationship between the probability of participating in microfinance program and the chosen independent variables. Since in the second stage, we model the expected values of y (TE, AE, EE), conditional on its being observed ($Z = 1$), we estimate the probit function three times (one for TE, one for AE and one for EE) and the results of first stage are then used to explain the influence of microfinance in the second stage. As efficient estimation of sample selection requires being able to identify some explanatory variables that affect the selection process but not the outcome equation (Greene 2006; Wooldridge 2002), we included land variable in the selection equation but not in the outcome equation. First, to model the selection equation and to obtain the results with which the outcome equation was compared, a probit selection equation was used as the dependent variable and five independent variables entered into the regression equation.

Age is one of the important determinants of participating in microfinance program, as expected. The uniform significant negative coefficient of age variable indicates that, higher age significantly decreases the probability to participate in microfinance program. Among the several other reasons that could explain the significant negative relationship between age and participating in the microfinance program is the fact that the older farmers may find it difficult to comply with the strict control and supervision of the microfinance program. On the other hand, young people are associated with the strict control and monitoring as well as paying the installments consistently under microfinance program, whereas the older farmers tend to stick to the less administered loans stemming from informal sources or from government subsidized loans.

Table 6: Estimated Probit Model for Participating in Microfinance Program

Variables	Probit Function		
	Coefficient (TE)	Coefficient (AE)	Coefficient (EE)
Constant	0.794*** (0.275)	0.737*** (0.273)	0.772*** (0.258)
Age	-0.011** (0.005)	-0.012** (0.005)	-0.011** (0.005)
Education	0.007 (0.046)	0.007(0.016)	0.0005 (0.015)
Land Size	0.023 (0.034)	-0.021 (0.045)	-0.043 (0.052)
Family size	-0.039 (0.041)	-0.023 (0.039)	-0.0406 (0.0399)
Household wealth	-0.791*** (0.327)	-0.762*** (0.356)	-0.825*** (0.297)
Accuracy of prediction (%)	68.72	68.72	68.72

Note: ***, **, and * indicate significant at 1% ($P < 0.01$), 5% ($P < 0.05$), and 10% ($P < 0.10$) level, respectively. Standard errors are in parentheses.

Farmers’ socioeconomic circumstances also significantly influence the probability to participate in the microfinance program. Specially, the results show that for wealthier household the probability to participate in microfinance program decreases significantly. The negative coefficient of land indicates that farms with larger land holdings are less likely to participate in the microfinance program. The result is consistent with a priori expectations in that it is widely hypothesized that agricultural microfinance program is basically meant for farmers with low land possession. However, there is no significant influence of farmers’ education and family size to participate in the microfinance program.

5.6. Results of the Determinants of Efficiency Corrected for Sample Selection

Table 7 presents the combined and independent effects of the variables used to determine the selection bias as well as presents the results of determinants of efficiency under participation to microfinance program. We also estimate a standard Tobit regression (Tobin, 1958) to illustrate the importance of

correcting for sample selection bias. Standard Tobit regression does not correct for selectivity bias (participation to microfinance program) whereas the corrected Tobit regression takes into account the selectivity issues. The dependent variables in these regressions are the efficiency index obtained from the VRS DEA model (Table 3) of the microfinance participants. To illustrate this method, Tobit sample selection model was used, TE/AE/EE was the dependent variable, and seven independent variables were entered simultaneously in the regression. The coefficient of the selectivity variable ($\rho_{u,\varepsilon}$) which measures the correlation between the errors in probit selection equation (equation 9) and the structure equation (equation 10) is significantly different from zero at 1% level under TE, AE and EE indices. The results suggest that serious selection bias exists and therefore justifies the use of sample-selection model in the determinants of efficiency model.

The standard Tobit regression that does not correct for selectivity bias shows a significant positive impact of household age on TE. But the age variable turned out to be negative and insignificant into the Tobit regression that corrects for the selectivity bias. The beta coefficient for this variable adjusts from 0.0026 to -0.0001. The negative adjusted coefficient of age indicates that for a microfinance participant the TE decreases as the age increases. This result is consistent with a priori expectation in that the managerial capability to carry out farming activities decreases with age. This finding is in line with Coelli and Battese (1996). Similarly the coefficients of education variable under TE and EE returned insignificant coefficients in the bias corrected Tobit regression compared to the standard Tobit regression. The result is in line with Wadud (2003). A plausible argument could be that five or more years of formal education are required before increases in efficiency could be observed (Table 1).

Results show that under TE, large family size had significant negative impact in the participation of microfinance program, and there is slight improvement in the regression coefficient for family size compared to the results initially obtained in the standard Tobit regression model without correction for selection bias (-0.0252 vs. -0.0218). The significant negative coefficient of family size on TE indicates that rice production in Bangladesh is labor intensive. To support large families, farm households find it difficult to optimally allocate funds between household consumption and farm operations. This results in the farm operations remaining inefficient from lack of timely funding.

Table 7: Estimates of the Determinants of Efficiency for Standard and Selectivity Bias Corrected Tobit Regression (Jointly Estimated with Probit Selection Equation⁷)

Variables	Standard Tobit regression			Estimates of Tobit regression corrected for selectivity bias		
	TE	AE	EE	TE	AE	EE
Constant	0.5122*** (0.0661)	0.5118*** (0.0492)	0.3367*** (0.0480)	0.6653*** (0.0805)	0.8330*** (0.0661)	0.5175*** (0.0636)
Age	0.0026* (0.0015)	-0.0005 (0.0011)	0.0005 (0.0010)	-0.0001 (0.0017)	0.00002 (0.0014)	-0.0018 (0.0014)
Education	-0.0067* (0.0035)	-0.0014 (0.0027)	0.0042* (0.0025)	-0.0036 (0.0041)	-0.0023 (0.0032)	-0.0016 (0.0034)
Family size	-0.0252*** (0.0095)	0.0060 (0.0071)	-0.0116* (0.0060)	-0.0218** (0.0107)	0.0019 (0.0089)	-0.0088 (0.0089)
Wealth	0.1204 (0.8471)	0.1191* (0.0633)	0.7940 (0.6173)	-0.231*** (0.089)	0.1841** (0.0815)	-0.1454** (0.0663)
On-farm training	0.1570*** (0.0302)	0.1175*** (0.0223)	0.1459*** (0.0217)	0.055* (0.0297)	0.013 (0.0227)	0.043** (0.0205)
Land	0.0110	0.00023	0.0033	0.0022	-0.0050	-0.0067*

⁷ Only the factors explaining efficiency is shown here for the microfinance borrowers. The counterpart is the non-borrowers of microfinance. The model selects the microfinance borrowers from the total sample (composed of both microfinance borrowers and non-borrowers) based on the information provided in the probit selection equation. The results of the non-borrowers are not presented here to save some space but are available on request from the authors.

fragmentation	(0.0073)	(0.0054)	(0.0053)	(0.0072)	(0.0052)	(0.0040)
Off-farm income share	0.4798*** (0.0416)	0.3272*** (0.0289)	0.3222*** (0.0286)	-0.0257 (0.0533)	-0.0652* (0.0400)	-0.1350*** (0.0348)
SIGMA (1)				0.2787*** (0.0286)	0.2165*** (0.0199)	0.2290*** (0.0155)
Selectivity bias ($\rho_{u,\varepsilon}$)				0.9713*** (0.0240)	-0.9439*** (0.0320)	0.9852*** (0.0124)
Number of selected observations	179	179	179	179	179	179

Note: ***, **, and * indicate significant at 1% (P<0.01), 5% (P<0.05), and 10% (P<0.10) level, respectively.

The coefficient of wealth returned a significant negative coefficient under TE and EE while the significant positive coefficient of AE had only a slight correction in the Tobit regression corrected for selectivity bias (i.e., 0.1191 vs. 0.1841). The significant positive coefficient of wealth under AE is consistent with a priori expectation in that microfinance participants with greater wealth tend to meet the expenditure constraints for production inputs thereby increasing their AE. Implicitly it also implies that wealthier participants are likely to self-finance their production operations thereby reduces their needs for credit. This finding is in line with previous studies (Simtowe et al., 2009). The estimated coefficients of on-farm training received displayed uniform significant coefficients in both models under TE and EE. However, the regression coefficients decreased a little bit in the corrected sample selection model. The significant coefficients indicate that the on-farm training enables the farmers to receive information on good farming practices and thus assists them to select input combinations in a cost minimizing way given their prices. On the other hand, on-farm training gives the farmers some technical knowledge on farming that may act as a vital means of increasing farming productive efficiency.

The coefficients of the number of plots operated turned out significantly negative under EE. It suggests that microfinance participants with less fragmented lands operate at higher EE levels and may apply new technologies such as tractor better and can manage the irrigation schemes better. This finding corroborates with previous studies (Wadud, 2003; Coelli and Battese, 1996). The policy implication of this finding is that farmers may be motivated to keep their land size larger to facilitate more efficient cultivation, irrigation, and harvesting. The significant positive relationship between off-farm income share and all efficiency indices turned out negative in the bias corrected models. The significant positive influence of off-farm income share under TE turned out negative but insignificant while the significant positive coefficients under AE and EE turned out to be significantly negative in the selectivity model. The levels of correction were quite high (0.48 vs. -0.03 for TE; 0.32 vs. -0.07 for AE and 0.32 vs. -0.14 for EE). However, the results indicate that the higher the off-farm hours a microfinance participant works, the less time is likely to be devoted to farming and thus resulting in higher inefficiency. The result is in line with Abdulai and Eberlin (2001).

6. Conclusions and Policy Implications

This paper applied DEA to calculate technical, allocative, and economic efficiencies of rice farms in north-central and north-western regions in Bangladesh and compared the efficiency estimates obtained from microfinance borrowers and non-borrowers. The main empirical result is that the TE and SE were quite high whereas the AE and EE are somewhat lower in all estimated models. Given the available technology microfinance borrowers and non-borrowers could increase their physical production by 27% and 29 % respectively whereas they could bring down the costs of production by 52% and 54 % respectively depending upon scale assumption.

The results of the pooled model and the non-discretionary DEA model are quite different. Comparing the results of non-discretionary model that takes into account the effect of external non-

discretionary inputs, with a formulation that only accounts for discretionary inputs (pooled DEA model) show that efficiency estimates improves in the presence of external non-discretionary factor. In particular, when the effect of external environment is taken into account, microfinance participants increased their relative TE, AE and EE by 7%, 2% and 7% respectively under VRS DEA model. It is thus evident that non-discretionary factors in relative efficiency analyses are such factors-although uncontrollable by the DMUs-still impacts the relative efficiency rankings.

The estimates of TE, AE and EE in the pooled sample, microfinance borrowers and non-borrowers model, and non-discretionary DEA model imply that inefficiency effects are present in the production. Results reveal that factors that influence TE, AE and EE under standard Tobit models that do not address selectivity bias are different from those that take into account the selectivity bias. Results demonstrate that after effectively correcting for selectivity bias, household size, land fragmentation (e.g., number of plots) access to on-farm training, household wealth and off-farm income share (out of total household income) are the main determinants of efficiency. Results of *t*-tests statistics showed that there are significant differences in the averages of AE and EE of both groups. The research has demonstrated that agricultural microfinance offered at reasonable cost may help the program participants in using the inputs in cost minimizing way. Thus the results of the study suggest that policies leading to ensuring access to microfinance, motivating the farms to preserve the agricultural land, raising farmers' educational level, encouraging farmers to receive on-farm training would increase overall efficiencies. Moreover, government can coordinate, support and become actively involved in agricultural microfinance through integrating it in the national agricultural credit policies as an agricultural development strategy in Bangladesh.

If these socio-economic and institutional factors are addressed in national agricultural policy formulation, they may push the farmers' production frontier upward in the long run which may reduce inefficiencies on one hand and lead to food security through increased production on the other hand.

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