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Impact of Microcredit on Agricultural Farm Performance and Food Security in Bangladesh

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Abstract

Microcredit is assumed to be likely to contribute both directly and indirectly to agricultural farm performance, farm output, poverty reduction and food security in Bangladesh. In this research, we study the impact of microcredit on farm performance, output and food security using farm level survey data from Rangpur, Dinajpur, Bogra and Rajsahahi districts of northern Bangladesh. The survey is conducted on 682 farms of which 450 are microcredit receivers and the rest 232 are microcredit non-receivers. We apply the Cobb-Douglas stochastic frontier and data envelopment analysis (DEA) along with inefficiency effects model and propensity score matching (PSM) techniques to assess the effects of microcredit on farm performance, output and food security.

Results from the stochastic frontier model indicate that farms are operating at decreasing returns to scale and inefficiency effects are significant in explaining total variability in output. Inefficiency effects model reveals that microcredit, as well as experience and education of farmers help them utilise inputs more efficiently. Level of efficiency of microcredit receiving farms is, on an average, one per cent higher than the microcredit non-receiving farms. Farms could, on an average, reduce their production cost around 19 per cent if they could operate at full efficiency levels and hence increase farm output. This contributes to the increase in farm output which increases food supply on the one hand and increases purchasing power on the other hand and thus, strengthens food security.

We compare the average income of farms that received microcredit to that of control group to find the impact of microcredit using propensity score matching (PSM) technique. Results show a positive impact of microcredit on farm income which subsequently could contribute to strengthening food security. The average income of microcredit receiving farms is 9.46 per cent higher than that of microcredit non-receiving farms.

Policy suggestions that follow include expansion, timely and fair distribution of microcredit to marginal and small farmers could lead to improvement of farm performance and farm output. This would in turn contribute to the reduction of poverty and to the betterment of food security.

Keywords: Microcredit, Farm Performance, Stochastic Frontier, Propensity Score Matching, and Food Security

JEL Classification Number: Q12, Q19

1. Introduction

Agriculture, which is the main supplier of food, is a very important sector in Bangladesh. This sector includes crops, fisheries and livestock. Rice is the principal staple food in Bangladesh. Agriculture in Bangladesh is characterised by large number of small and marginal farms with limited financial resources and hence they cannot apply optimal inputs and new production technologies for higher production. This results in lower production and productivity in agriculture sector hampering food security. Timely and proper application of inputs like fertiliser, pesticides and irrigation is important for higher production. Therefore, cash for the purchase of seeds, chemical fertilisers, pesticides and mechanical equipments is of utmost importance. It can be mentioned that small and marginal farms constitute most of the total land holdings in Bangladesh.

Food is the most basic human need. Food security can be broadly defined as existing when all people at all times have availability of and access to sufficient, safe and nutritious food. One essential element of food security is to ensure sustained availability of food to meet all people's demand at prices commensurate with their income. A key aspect of long-term food security is promotion of efficient and sustained domestic food production.

Bangladesh has consistently faced the problem of food deficit. With high and rising food prices and inadequate availability of food in the world market, food security of Bangladesh is increasingly threatened. Also, low income and periodic collapse of purchasing power through loss of job in certain areas of Bangladesh greatly reduce affordability of food. So, it has become imperative to devise means to tackle this situation.

Increasing food production and attaining food security in Bangladesh require timely and adequate supply of agricultural inputs including agricultural credit. The farmers in the rural areas require financial support from institutional and non-institutional sources to meet the expenses of various agricultural activities. With very low level of income it is difficult for them to accumulate capital for meeting the production expenditure. As such, a large number of farmers in rural Bangladesh are dependent on credit. For accumulation of capital for various productive activities as well as for sustaining livelihood, the poor farmers seek credit provided by institutional and non-institutional sources. Considering credit as a crucial factor in ascertaining sustainable development of the agricultural sector, it is necessary to find ways in which farmers' access to credit can be ensured.

As marginal and small farmers have little or no access to formal sources of credit, microcredit can provide them access to purchase of inputs like seed, fertiliser and irrigation at proper time. This, in turn, helps use of new production technologies thereby, increasing food production and ensuring food security.

Agricultural growth is crucial for alleviating rural poverty. Access to institutional credit to farmers and appropriate quantity and quality of agricultural credit are crucial for realising the full potential of agriculture as a profitable activity.

Recently, the Government of Bangladesh, Palli Karma-Sahayak Foundation (PKSF), and other institutions have started funding in agricultural activities. Use of microcredit in agriculture[1] has been on the increase and now it constitutes about 40 percent of all credits

[1] Microcredit in agriculture is provided to farmers who have own land up to 2.5 acres (5.00 acres including sharecropping land) although microcredit is generally given to those having land up to 0.5 acre.

that the farmers receive. A priori, it is thought that microcredit could have a positive impact in enhancing efficiency performance of farms, and hence raise farm income and food security of marginal and small farmers and reduce poverty. It has, therefore, become necessary to study the impact of microcredit on efficiency performance of farms and agricultural production. The research is designed to conduct a thorough study to assess the impact of microcredit on farm performance, agricultural production and food security.

1.1. Objectives of the Study

Microcredit can have double-edged impact on food security. By extending microcredit to farmers, the level of inefficiency in crop production can be reduced and supply of food increased. This helps availability of food. Extension of microcredit to the farmers can increase their income through provision of job in dire times that improves access to food. Thus microcredit helps reduce poverty through an increase in food production (availability) and increase in purchasing capability (access) of the farmers. The specific objectives of this study are to:

(i) assess improvement of availability of food through reduction in crop production inefficiency of farms in Bangladesh;

(ii) examine the role of microcredit in raising productive efficiency;

(iii) assess the role of microcredit in augmenting food affordability;

(iv) make appropriate policy suggestions for ensuring better food security;

(v) examine the link between microcredit, food security and poverty alleviation.

This research applies the Stochastic Frontier Analysis (SFA), Data Envelopment Analysis (DEA) method and Propensity Score Matching Techniques to analyse the impact of microcredit on agricultural farm performance and food security.

2. Review of Literature

We give a review of the works on food security relevant to this study. We first survey the papers that dealt with crop production efficiency and inefficiency, food security and propensity score matching methods.

Latif (2001) examined the relationship between microcredit and savings of rural households in Bangladesh. He derived his data for this study from a follow-up household survey on “Credit Programmes for the Poor” jointly conducted by the Bangladesh Institute of Development Studies and the World Bank. He found that the microcredit programmes of the MFIs, targeted to alleviate poverty by supplying small credit to rural poor in self-employment activities, had a distinctly positive role in influencing household savings. The results from estimated regression models also showed that participation in credit programmes had statistically significant and quantitatively important influence on household savings. He concluded that microcredit programmes should continue and should be extended to the landed category as well.

Javed, *et al*. (2006) evaluated the impact of microcredit of PRSP on productivity of wheat and sugarcane in Faisalabad, Pakistan. Results of this study showed that microcredit was effective in increasing crop production and improving the living standard of the farmers in the selected areas. Regression analysis indicated that credit and fertiliser significantly affected production. They concluded that microcredit facilities should be expanded to a greater number of crop producers.

Hakim (2004) discussed the relationship between microcredit and agriculture. He observed that small and marginal farmers, who constitute the majority of farming population, are multi-occupational, productive and efficient. This study shows that microcredit providers should extend their priority area of lending to cover small and marginal farmers.

There are a number of studies that examined the efficiency of rice farmers in developing economies as well as some on Bangladesh (Banik, 1994; Sharif and Dar, 1996; Wadud and White, 2000; Thiam *et al.*, 2001; Coelli *et al.*, 2002). These studies applied the stochastic frontier analysis (SFA) and the data envelopment analysis (DEA) and estimated farming efficiency.

In a study of technical efficiency, Banik (1994) reported a value of 82 per cent efficiency for a sample of 99 *boro* modern variety (MV) rice farmers. Using a Cobb-Douglas functional form, Sharif and Dar (1996) reported several mean estimates of technical efficiency for a sample of 100 farms. For *aman* rice, farmers were found to be over 90 per cent technically efficient. These results on efficiency are perceived to be rather high.

Wadud and White (2000) employed both DEA and SFA to examine the technical efficiency of a sample of 150 farmers in Bangladesh. For translog SFA, they found technical efficiency to be 79 per cent, whilst for DEA it was 79 per cent under constant returns to scale and 86 per cent under variable returns to scale. For SFA, they reported that the sample of farms exhibited decreasing returns to scale.

In addition to measuring farm level efficiency, much of the 'frontier literature' also attempted to statistically explain any observed inefficiency, and a varied assortment of variables has been used for this. For example, for a sample of wheat farmers in Pakistan, Battese and Broca (1997) found education level to be positively related to technical efficiency, and tenancy and credit availability negatively related. However, other results examining the effect of education on farm level efficiency in the literature are mixed.

Phillips (1994) provided a detailed review of the influence of education on farmer efficiency. In a meta-analysis of existing research he found that education positively influenced productivity and this was especially so in Asia compared to Latin America. Huang and Kalirajan (1997) supported this finding for rice production in China. For Bangladesh, Sharif and Dar (1996) examined how education, growing experience, and farm size influenced technical efficiency for *boro* modern variety rice using a two-step procedure, and found that education was positively related to technical efficiency.

In contrast to the results mentioned above, Wadud and White (2000) found that their model yielded a negative but statistically insignificant estimate for education in terms of explaining efficiency. They also found that access to irrigation infrastructure (diesel-power and rural electrification) improved technical efficiency, and that environmental degradation (measured as soil quality) reduced it. Coelli *et al.* (2002) employed a comprehensive set of variables in a second stage Tobit regression to explain technical efficiency for both *aman* and *boro* rice production, but found few statistically significant estimates. This may have been the result of including too many explanatory variables resulting in problems of multicollinearity. Simar and Wilson (2003) have identified significant technical shortcomings with the two-stage approach that stems from the upward bias in technical efficiency estimates of DEA.

Omonona and Agoi (2007) studied food security situation among Nigerian households using primary data. They found that the food insecurity incidence for the study area was 0.49. Food insecurity incidence increased with increase in age of household heads. They also found that food insecurity decreased as income increased. Another interesting result of their study was that food insecurity decreased with increase in the level of education.

Akinsanmi and Doppler (2005) examined various aspects of food insecurity of Nigerian households. They particularly looked into ownership and access to resources such as land, labour and capital, and the impact of these on family living standard and household food security (supply and access). They found that the farming systems in highly populated areas had relatively smaller resources and capacity base, were crop oriented and had a lower living standard. They sold more of their outputs but purchased less to meet household food supply. The farming systems located in low/medium populated areas spent more on market supply purchases though they had more land resources.

Siamwalla and Valdas (1994) studied food security in developing countries. They provided important estimates of the state of food security in different countries. They dealt with the matters as international issues providing comparison and relative position of different developing countries.

Golait (2007) analysed the issues in agricultural credit in India. The analysis reveals that the credit delivery to the agriculture sector continues to be inadequate. It appears that the banking system is still hesitant on various grounds to purvey credit to small and marginal farmers. The situation calls for concerted efforts to augment the flow of credit to agriculture, alongside exploring new innovations in product design and methods of delivery, through better use of technology and related processes. Facilitating credit through processors, input dealers, NGOs, etc., that are vertically integrated with the farmers, including through contract farming, for providing them critical inputs or processing their produce, could increase the credit flow to agriculture significantly.

Zaman (1999) explored the relationship between microcredit and the reduction of poverty and vulnerability by focusing on BRAC, one of the largest microcredit providers in Bangladesh. This paper argued that microcredit contributes to mitigating a number of factors that contribute to vulnerability, whereas the impact on income-poverty is a function of borrowing beyond a certain loan threshold and to a certain extent contingent on how poor the household is to start with. Consumption data from 1072 households is used to show that the largest effect on poverty arises when a moderate-poor BRAC loanee borrows more than BDT 10000.00 ($200) in cumulative loans. A number of pathways by which microcredit can reduce vulnerability, namely by strengthening crisis-coping mechanisms (the 1998 flood in Bangladesh is used as a case study), building assets and ‘empowering’ women are discussed. Data from 1568 women are used to construct 16 ‘female empowerment’ indicators and the empirical analysis that follows, suggests that microcredit has the greatest effect on female control over assets and also on her knowledge of social issues controlling for a host of other characteristics.

Islam (2008) evaluated the impact of microfinance on household consumption using cross-section data set from Bangladesh. The richness of the data and programme eligibility criterion allow the use of a number of non-experimental impact evaluation techniques, in particular instrumental variable (IV) estimation and propensity score matching (PSM). Estimates from both IV and PSM strategies have been interpreted as average causal effects that are valid for various groups of participants in microfinance. The overall results indicate that the effects of micro loans are not robust across all groups of poor household borrowers. It appears that the poorest of the poor participants are among those who benefit most. The impact estimates are lower, or sometimes even negative, for those households marginal to the participation decision. The effects of participation are, in general, stronger for male borrowers. These results hold across different specifications and methods, including correction for various sources of selection bias (including possible spill-over effects).

Pufahl and Weiss (2007) applied a non-parametric propensity score matching approach to evaluate the effects of two types of farm programmes (agri-environment (AE) programmes and the less favoured area (LFA) scheme) on input use and farm output of individual farms in Germany. The analysis reveals a positive and significant treatment effect of the LFA scheme for farm sales and the area under cultivation. Participants in AE schemes are found to significantly increase the area under cultivation (in particular grassland), resulting in a decrease of livestock densities. Furthermore, participation in AE programmes significantly reduced the purchase of farm chemicals (fertiliser, pesticide). We also find substantial differences in the treatment effect between individual farms (heterogeneous treatment effects). Farms which can generate the largest benefit from the programme are most likely to participate.

Adebayo and Adeola (2008) examined the role of credit in agricultural economy and its constraint which can affect farmer's investment behaviour in Surulere Local Government area of Oyo State. 120 respondents randomly selected from 20 villages were interviewed using structured questionnaire. The study found that most of the respondents obtained loans through informal sources with co-operative societies being the most popular source. The results also showed that payment for labour wages consumed the larger percentage of the credit obtained by most of the respondents. Accessibility to agricultural credit was constrained by certain factors identified in the study. However, to ensure effective utilisation of available sources of credit, establishment of agricultural and community banks in the rural areas with simple procedures of securing loans was recommended. Also, mobilisation of farmers into formidable groups in order to enjoy the benefit of collective investment of group savings was also recommended.

Andersson *et al.* (2008) studied efficiency in shrimp farming in a rural region in Bangladesh where formal micro-lending is well established, but where more expensive informal micro-lending coexists with the formal schemes. Both farmers who exclusively use formal loans and those who also use informal loans, are credit constrained; both types over-utilise labour in order to reduce the need for inputs that require cash at the beginning of the season, creating inefficiencies in production. However, the credit constraint is actually milder for the informal borrowers; the implicit shadow price of working capital is substantially higher in the group that only takes formal loans than in the group that also uses informal loans. Results suggest that, even in areas where formal micro-lending has existed for a long time, access to credit remains a problem for many smallholders. Moreover, informal lenders – with their closer ties to the individual farmers – remain more successful in identifying those smallholder farmers that are most likely to make the best use of the borrowed funds. Thus, although formal microcredit schemes avoid one of the problems of traditional formal lending – the high administrative fees that create barriers to small loans – they do not necessarily solve the problem of how to select successful borrowers. Informal lenders have an information advantage that formal microlenders lack. Formal lenders need to find routes for accessing this information in order for formal microcredits to succeed.

Dehejia and Wahba (1999), and Smith and Todd (2005) directly compared the results of matching and regression estimates and showed that avoiding functional form assumptions can be important to reduce bias.

Caliendo and Kopeinig (2008) discussed the implementation issues of propensity score matching (PSM) and gave some guidance to researchers who want to use PSM for evaluation purposes.

There are very few works that have formally linked credit and efficiency performance of farms (Battese and Broca, 1997). To our knowledge, there is no study that has linked microcredit and farm efficiency, and the resulting improvement in food security in Bangladesh and elsewhere. That is why we could not indicate or highlight any research work showing relationship between microcredit and efficiency estimates in our literature review.

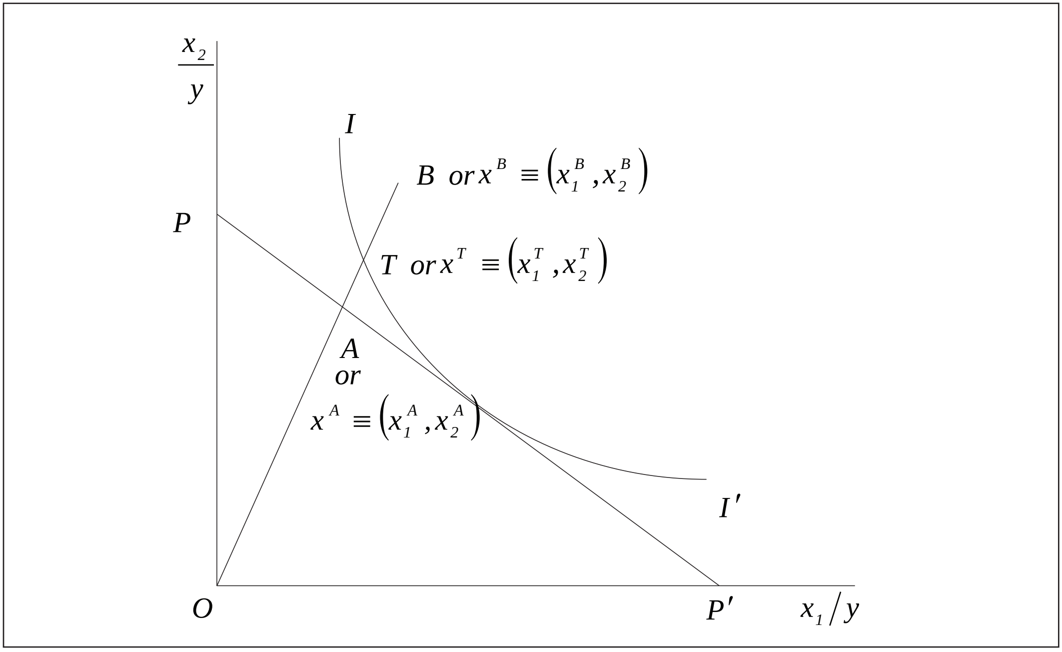
3. Agricultural Efficiency Performance: Some Theoretical Issues

We discuss production functions and some related concepts which form the basis of measuring the agricultural efficiency performance of farms in this section. The measurement of efficiency begins with Farrell (1957). The failure to produce the maximum output from a given input mix at minimum cost results in inefficiency. Inefficiency is explained by, inter alia, restricted access to technology, a lack of knowledge, restricted access to extension services, an inappropriate scale of production and sub-optimal allocation of resources. The efficiency of a farm consists of two components: technical and allocative efficiency. Technical efficiency concerns the ability of a farm to produce maximum output from a given set of inputs using existing technology.

To explain diagrammatically, the concept of technical efficiency considers the production activity of a farm, following Kopp and Diewert (1982). In Figure 1, assume that the farm uses two inputs x_1 and x_2 to produce a single output y, and that the production technology is

Figure 1

Measures of Technical Efficiency



summarised by a linearly homogeneous production function following Farrell. The frontier unit isoquant for this technology and an inefficient production activity are depicted by II', and B respectively. Along the ray OB, the production activity, denoted by T and defined by the intersection of line segment OB with the isoquant II', represents a technically efficient input combination as it lies on the frontier isoquant. The technical inefficiency of the farm producing at point B is represented by the distance TB because this is the amount by which both inputs could be proportionally reduced producing the same level of output. In percentage terms, this is usually written as the ratio TB/OB.

The technical efficiency of the farm operating at point B is expressed as:

$$TE = \frac{OT}{OB} = 1 - \frac{TB}{OB} = 1 \quad \text{Technical inefficiency } (0 \leq TE \leq 1).$$

The farm operating at point T is fully technically efficient farm because it is located on the efficient and frontier isoquant, and $TE = 1$.

Farrell's radial measures of efficiency are originally characterised by constant returns to scale and these measures have been generalised to less restrictive technologies by Fare and Lovell (1978) and Forsund and Hjalmarsson (1979).

4. Data and Survey

An analysis of agricultural farm efficiency performance, farm production and food security on a micro level requires farm level survey data. Since this study examines the role of microcredit in enhancing agricultural productive efficiency and food security, data on microcredit are needed. Keeping in mind the objectives and methodology of the research we prepared the questionnaire to collect required information and data. We collect those data and information through a field survey.

The northern Bangladesh, by which is meant the Rajshahi division, which is our study area, has 16 districts from which we select four districts. We selected the Palasbari Upazilla of Gaibanda district of greater Rangpur, Ghoraghat Upazilla of Dinajpur district of greater Dinajpur, Mohonpur Upazilla of Rajshahi district of greater Rajshahi, and Kalai, Khetlal and Joypurhat Sadar Upazillas of Joypurhat district of greater Bogra.[2]

From these upazillas, 149 villages are selected based on purposive sampling to examine the impact of microcredit. Farms of these villages constitute the sampling frame from which 682 samples are taken. From these 682 samples, 450 are microcredit users who constitute the treatment group and the remaining 232, who have not taken microcredit for agricultural and other purposes, constitute the control group which even has not received any other credit from other sources. So, we have two sub-samples – one composed of those farmers who have taken microcredit and another composed of those who have not. Samples for both control and non-control groups are drawn from farmers having similar socioeconomic conditions.

We designed a comprehensive questionnaire which aims to achieve two goals. The first is to gather data relevant to the objectives of the survey and the second to gather data which are reliable and valid. These goals can be called relevance and accuracy (Warwick

[2] We took help from the list of microcredit-providing NGOs under MFMSF project supplied by the Institute of Microfinance (InM) to finally select the survey areas and farms households.

and Lininger, 1975). The questionnaire included questions about household characteristics such as experience, education, household size, social status of the farm households and so on. The survey had questions about microcredit taken and the purpose of the microcredit.

The questionnaire contained a number of personal questions discussing name, age, marital status and demographic characteristics. The survey covered output and input information of farm activities and their prices. The inputs included land, labour, machinery, fertiliser, seed and irrigation. Questions regarding the use of inputs and their prices were included in the questionnaire. A number of questions collected data and information on total land owned, total cultivable land, homestead area, forest area, total cultivated area, net cultivated area, total irrigated area, number of plots, average plot size, average plot distance, sharecropping area and homestead utilisation.

A total of 682 completed questionnaires from four districts have been obtained of which 450 are microcredit receivers and the rest 232 are microcredit non-receivers. Table 1 shows the number of microcredit receiving and non-receiving households of four districts.

Table 1

Total Number of Household Head Surveyed

Serial No.	Name of District	Number of Households		
		Microcredit Receiver	Microcredit Non-receiver	Total
1	Rangpur	111	60	171
2	Dinajpur	110	61	171
3	Rajshahi	111	59	170
4	Bogra	118	52	170
Total		450	232	682

From the Palasbari Upazilla of Gaibanda district of greater Rangpur, we collected data and information from 175 household heads spreading over five villages. Of 175 questionnaires that were filled in, four were rejected because of various deficiencies such as incompleteness and inconsistency. The name of villages and number of household heads surveyed are shown in Appendix 1. Of 171 surveyed households, 111 were microcredit receivers and 60 were microcredit non-receivers.

From the Ghoraghat Upazilla of Dinajpur district of greater Dinajpur we conducted the survey on 175 household heads and obtained 171 fully completed questionnaires. The survey in this district spread over 29 villages. The name of villages and number of household heads surveyed are given in Appendix 2. Of 171 surveyed households, 110 were microcredit receivers and 61 were microcredit non-receivers.

In Rajshahi district, we have selected 170 completed questionnaires although we conducted the survey to 175 households. The rest five were rejected because of various deficiencies. Appendix 3 shows the number of villages and households surveyed in Mohonpur Upazilla of Rajshahi district of greater Rajshahi. Of these 170 surveyed households, data and information were collected from 111 credit receivers and 59 credit non-receivers.

In greater Bogra district, we selected Joypurhat Sadar, Khetlal and Kalai upazillas of Joypurhat district. We collected data and information from 175 household heads, of which 6 were rejected leaving 169 household heads for final analysis. Of these, 117 were microcredit receivers and the rest 52 were non-receivers. The name of villages and number of household heads surveyed are given in Appendix 4 - 6. Although the total number of samples is about the same as in all districts, for Bogra the samples were drawn from three upazillas rather than one upazilla as in the other districts. This is because of wide spread of microcredit receivers having similar characteristics across different villages numbering 83.

In Joypurhat Sadar Upazilla, data and information were collected from 82 household heads, of whom 62 were microcredit receivers and the rest 20 were microcredit non-receivers. The survey spread over 33 villages of the Upazillas. This is shown in Appendix 4.

A total of 43 questionnaires was filled in to obtain data and information covering 35 villages in Kalai Upazilla of Joypurhat district. Of 43 households, 26 received microcredit and 17 did not, which is given in Appendix 5.

We covered 25 villages and collected data and information from 30 microcredit receciving household heads and 15 microcredit non-receiving household heads from Khetlal Upazilla in Joypurhat district. Appendix 6 provides a description of the Khetlal Upazilla.

We presented households according to distribution of farm size and microcredit received. These are given in Appendix 7 and 8. We found in Appendix 7 that most of the farm households, 226 out of 682 households had farms between 0.5 and 1.00 acre, 155 farm households cultivated land between 0 and 0.5 acres and 89 farm households had cultivated land above 2.00 acres including sharecropping land. We also found in Appendix 8 that 250 out of 450 marginal and small farms received an amount of microcredit up to BDT 10000.00. It also showed that 182 farms received microcredit up to BDT 20000.00. Only 20 farms received microcredit above BDT 20000.00.

5. Empirical Methodology

There are four major elements of food security. These are food availability, food access, food utilisation and stability (not losing such access). In a larger sense two broad groups of factors – supply and demand determine food security. In this study, we examine existing inefficiency in farm production and factors associated with such inefficiency that include use of microfinance. The reduction in such inefficiency will lead to the increase in farm production and hence food security. This evaluates the impact of microcredit on farm production and food security.

The stochastic frontier analysis (SFA) and data envelopment analysis (DEA) models are applied to estimate technical efficiency performance of farms. Inefficiency effects models will be applied to identify and quantify factors, such as microcredit, which could affect the efficiency performance of farms. We also apply propensity score matching (PSM) technique to evaluate the likely positive impact of microcredit on farm output and food security. The SFA, DEA models and PSM techniques are briefly described below.

5.1. Stochastic Frontier Analysis (SFA), Efficiency Measurement and Effect of Microcredit

The SFA model has two parts. The first part deals with production structure as manifested in the use of physical inputs. The second part, which is the more interesting one, deals with factors that could influence production but which are not included in the production function. One such factor is microcredit. The model is very versatile in that besides giving an aggregate measure of efficiency, it also gives efficiency performance measures for each farm.

The seminal paper of Farrell (1957) on efficiency pioneered the development of different approaches to efficiency measurement. The stochastic econometric frontier is one of the two main methods of measuring efficiency. The econometric approach includes both the stochastic econometric frontier (SF) and the deterministic frontier. The deterministic frontier approach does not allow for a stochastic random error component in the error term and hence is subject to the criticism that all deviations from the frontier are attributed to inefficiency. Accordingly, we focus on the stochastic econometric frontier approach to measuring efficiency performance.

Production function models estimated by OLS assume that farms maximise expected profit so that a stochastic error term, with zero mean, accounts for the difference between observed and expected output and are ascribed to factors outside the control of the farmers (Zellner *et al.*, 1966). Thus, all farms are equally efficient. However, it is unlikely that all farms are equally efficient. Productivity differs because of differences in technology, the efficiency of the production process, and the environment in which production process happens (Lovell, 1993), and managerial ability (Dawson and Lingard, 1982). A frontier production function relaxes the assumption of equal efficiency and hence relaxes the assumption of stochastic error terms with zero means.

The general stochastic frontier production function model, independently proposed by Aigner *et al.* (1977) and Meeusen and van den Broeck (1977), decomposes the composed error term into two components: a stochastic random error component and a technical inefficiency component. This approach is closer to the theoretical production function, which gives the maximum output from a given input mix, than the average production function and is more realistic than the deterministic frontiers of Farrell (1957) and Aigner and Chu (1968).

The stochastic approach attempts to distinguish the effects of stochastic noise from the effects of inefficiency. Addressing the stochastic noise problem associated with the deterministic frontier, and statistical hypothesis testing are the main strengths of the stochastic frontier approach; assumptions regarding the parametric functional form for the frontier technology and the distributional assumptions for the technical inefficiency term are its major drawbacks. Coelli (1995) provides a review and critique of the recent developments and applications of frontier techniques of efficiency measurement. Comprehensive reviews of the various stochastic frontier functions and econometric estimation of frontiers are provided also by Førsund *et al.* (1980), Schmidt (1985), Bauer (1990), Battese (1992), Brevo-Ureta and Pinheiro (1993), Fried *et al.* (1993), and Greene (1993).

Most empirical applications of stochastic frontiers in agriculture have investigated the sources of farmer technical inefficiency using a two-stage approach (for example, Tadesse and Krishnamoorthy, 1997; Hallam and Machado, 1996; Parikh and Shah, 1994). The first stage estimates a stochastic frontier by maximum likelihood techniques and calculates the technical efficiency for each farm under the assumption that these inefficiency effects are identically distributed. Once technical inefficiency is estimated, it is further regressed in the second stage on a set of farm-specific factors that may explain differences in technical inefficiency among farms using OLS. This two-stage approach, using a stochastic frontier, the second stage on a set of farm-specific factors that may explain differences in technical inefficiency among farms using OLS. This two-stage approach, using a stochastic frontier, has been applied by Kalirajan (1981) and Pitt and Lee (1981) and by Heshmati and Kumbhakar (1997) for pseudo panel data, and Sharma *et al.* (1999) for cross sectional data. Timmer (1970) was one of the first to apply this approach *albeit* using covariance analysis in stage one.

The general stochastic frontier production model is defined as:

$$y_i = f(x_i;\beta)e^{u_i} \tag{1}$$

$$u_i = \xi_i - \zeta_i, \quad i = 1,2,3,\ldots,q, \qquad -\infty \le \xi_i \le \infty \text{ and } \zeta_i \ge 0.$$

where y_i represents the output of the ith farm, x_i denotes a vector of q inputs, and β denotes the parameters. The error term, u_i, is decomposed into a stochastic random disturbance and an asymmetric non-negative random error term. The stochastic random disturbances, ξ_i, the symmetric random errors, take account of measurement error and capture exogenous shocks and other factors not under the control of the farmers; ξ_i, can take any real value and when added to the deterministic frontier, $f(x_i;\beta)$, gives rise to the stochastic frontier. The asymmetric non-negative random errors, ζ_i, which are called technical inefficiency effects, account for technical inefficiency in production. When $\zeta_i = 0$, the production function is the best-practice frontier which yields the maximum output given the inputs; and when $\zeta_i > 0$, output is less than this maximum due to technical inefficiency. The greater the quantity by which the actual output falls short of the stochastic frontier output, the higher the level of technical inefficiency. The observed differences in output can be attributed to either technical inefficiency or stochastic disturbances or both. A model without ζ_i is the average frontier model criticised by Farrell (1957). Further, a model without the random component, ξ_i results in a deterministic or full frontier model and can be estimated by linear programming techniques.

Assuming a probability density function for both ξ_i and ζ_i, we can estimate (1) by maximum likelihood methods. This approach yields a means by which we can statistically examine the sources of differences between the farmer's output and the frontier output by calculating the variance parameters which relate the variance of ξ_i to the composed variance of u_i (Kalirajan, 1981).

The variance parameters are expressed as:

$$\sigma_u^2 = \sigma_\xi{}^2 + \sigma_\zeta{}^2, \qquad \gamma = \sigma_\zeta^2 \big/ \sigma_u^2 \quad \text{and} \quad 0 \le \gamma \le 1 \tag{2}$$

Battese and Corra (1977) define γ as the total variation of output from the production frontier which can be attributed to technical efficiency. If $\gamma \to 0$ then $\sigma_\zeta^2 \to 0$ and, which implies that the symmetric error term ξ_i dominates the composed error term and output differs from the frontier output mainly due to measurement errors and the effect of other external factors on production. If $\gamma \to 1$ then $\sigma_\xi^2 \to 0$ and $\sigma_\zeta^2 \to \sigma_u^2$ which indicates that the asymmetric non-negative error term ζ_i dominates the composed error and the differences between observed output and frontier output can be attributed to differences in technical efficiency.

The technical efficiency of the ith farm is defined as the ratio of the observed output to the corresponding frontier output, given the levels of the inputs. The farm-specific technical efficiency, φ_i , can be measured as:

$$\varphi_i = \frac{y_i}{y_i^*} = \frac{f(x_i, \beta)e^{(\xi_i - \zeta_i)}}{f(x_i, \beta)e^{\xi_i}} = e^{-\zeta_i} \qquad 0 \le \varphi_i \le 1$$

Alternatively, φ_i is defined as the ratio of the mean of production (given x_i and ξ_i) to the corresponding mean of production if there is no technical inefficiency (Battese and Coelli 1988):

$$\varphi_i = \frac{E(y_i | x_i, \zeta_i)}{E(y_i | x_i, \zeta_i = 0)}$$

Again if the systematic random error, ξ_i, is assumed to be independently and identically distributed with mean zero and variance and the technical inefficiency term is half-normally distributed, the farm-specific technical efficiencies and mean technical efficiency are obtained respectively as:

$$\varphi_i = E\left[e^{-\zeta_i | u_i}\right] = 1 - \Phi(\sigma_i^*)e^{\frac{1}{2}\sigma_i^{*2}} \text{ and } \overline{\varphi_i} = 1 - \Phi(\sigma^*)e^{\frac{1}{2}\sigma^{*2}} \text{ (Jondrow \textit{et al.}, 1982).}$$

Again the systematic random error, ξ_i, is assumed to be independently and identically distributed with mean zero and variance, σ_ξ^2; and ζ_i are non-negative truncations of the $N(\mu, \sigma_\zeta^2)$ distribution,

where: $\mu = z_i \delta_i$ (3)

and z_i is a $(k \times 1)$ vector of variables like microcredit, experience and education of farmers and land fragmentation, which may influence efficiency and δ_i is an $(1 \times k)$ vector of parameters. Measurements of the farm-specific efficiency, $e^{-\zeta_i}$, depends upon the decomposition of u_i, which is derived from the conditional expectation of $e^{-\zeta_i}$ given u_i. Thus the technical efficiency of each farm is given by:

$$\therefore \quad \varphi_i = \left[\frac{1 - \Phi\{\sigma_i^* - (\mu_i^* / \sigma_i^*)\}}{1 - \Phi(-\mu_i^* / \sigma_i^*)}\right] e^{\left(-\mu_i^* + \frac{1}{2}\sigma_i^{*2}\right)} \qquad (4)$$

which produces the measure of technical efficiency given the specification of the frontier production function model and the inefficiency effects model. Technical inefficiency is estimated by $1 - E\left\{e^{-\zeta_i | u_i}\right\}$. The mean technical efficiency of all farms in the sample, $\overline{\varphi}$, is obtained as:

$$\overline{\varphi} = \left[\frac{1 - \Phi\{\sigma^* - (\mu^* / \sigma^*)\}}{1 - \Phi(-\mu^* / \sigma^*)}\right] e^{\left(-\mu^* + \frac{1}{2}\sigma^{*2}\right)}$$

We calculate the maximum likelihood estimator of the predictor for the technical efficiency that is based on the conditional expectation of $e^{-\zeta_i}$ given the composed error term of the stochastic frontier production model (Battese and Coelli, 1988). The parameters of the coefficients of stochastic frontier model, β, and the technical inefficiency effects model, δ_i, along with the variance parameters are also estimated.

The log-likelihood function for the sample observations is:

$$L\left(\Omega^*, y\right) = \sum_{i=1}^{n} \ln\left[1 - \Phi\left(-\mu_i^* / \sigma_{i\zeta}^*\right)\right] - \frac{1}{2}\sum_{i=1}^{n}\left[\left\{y_i - f\left(x_i;\beta\right)\right\}'\left\{y_i - f\left(x_i;\beta\right)\right\} / \sigma_{\xi}^2\right] - \frac{1}{2} n\left(\mu/\sigma_{\zeta}\right)^2$$

$$+ \frac{1}{2}\sum_{i=1}^{n}\left(\mu_i^* / \sigma_{i\zeta}^*\right)^2 - \frac{1}{2} n \ln(2\pi) - \frac{1}{2} n \ln\left(\sigma_{\zeta}^2 + \sigma_{\xi}^2\right) - n \ln\left[1 - \Phi\left(-\mu/\sigma_{\zeta}\right)\right]$$

where $\Omega^* \equiv \left(\beta', \sigma_{\xi}^2, \sigma_{\zeta}^2, \mu\right)'$

5.1.1. The Cobb-Douglas Stochastic Frontier Model

Several specifications of the stochastic frontier model have been developed. The Cobb-Douglas production stochastic frontier has been widely used in econometric analysis. We use the Cobb-Douglas production approach in this research.

$$\ln\ y_i = \beta_0 + \sum_{i=1}^{q} \beta_i\ \ln x_i \qquad (5)$$

where yi = output, β_0 is an "efficiency parameter", i.e., an indicator of the state of technology, x_i = inputs of production, $\ln$ = natural logarithm, β_i $(i=1,2,3,...,q)$ are the output elasticities with respect each input and the returns to scale is $\sum_{i=1}^{n} \beta_i$.

5.2. Data Envelopment Analysis (DEA) Method

Data envelopment analysis (DEA) is a non-parametric mathematical programming approach to frontier estimation which has been developed independently of the stochastic frontier approach over the past two decades. Charnes, Cooper and Rhodes (1978) reformulated this piecewise-linear convex hull approach to the estimation of technical efficiency and frontier models, to incorporate multiple-output and multiple-input technologies. Their approach assumes constant returns to scale (CRS) and is referred to as the CRS DEA model. This model is used here to assess the relative efficiency of homogeneous farms in transforming inputs into outputs.

Banker, Charnes and Copper (1984) extended the CRS model by relaxing the assumption of constant returns to scale to variable returns to scale (VRS). This model is known as the VRS DEA model. The VRS DEA model differs from the CRS DEA model in that it envelops the data more closely, thereby producing technical efficiency estimates greater than or equal to those from the CRS DEA model.

Coelli (1995) provides a review and critique of different DEA approaches.[3] DEA is both non-parametric and non-stochastic since it does not impose any a priori parametric restrictions on the underlying frontier technology (because it does not necessitate any functional form to be specified for the frontier technology) and it does not require any distributional assumption for the technical inefficiency terms. Therefore the method avoids the imposing of unwarranted structures on both the frontier technology and the inefficiency component that might create a distortion in the measures of efficiency (Färe *et al.*, 1995). The minimum

[3] Seiford and Thrall (1990), Bjurek *et al*. (1990), Lovell (1993, 1994), Charnes *et al.* (1995), Seiford (1996), and Ali and Seiford (1993) also review the non-parametric DEA approach.

assumptions required for this DEA frontier methodology are monotonicity and convexity of the efficient frontier (Banker *et al.* 1984).

DEA estimates efficiency relative to the Pareto-efficient frontier which estimates best performance (Murthi *et al.* 1997). Furthermore, DEA can obtain target values based on the best practice units (peers) for each inefficient farm that can be used to provide guidelines for improved performance. However, the major shortcoming of DEA is that it is deterministic and assumes a zero value for the stochastic random error component; thus technical inefficiency reflects all unexplained variations of agricultural production and the inefficiency of the observed farm is therefore biased upwards. Moreover, since there is no measurement error or other random noise and since it is nonparametric, efficiency measures can not be subjected to statistical tests.

The DEA frontier gives either the maximum output for a given input level or uses the minimum input for a given output level. Thus the analysis of efficiency can have an input-saving or an output-augmenting interpretation.

Assume that the i-th farm uses $x_i = \{x_{ki}\}$ of inputs $(k = 1,2,3,...,6)$ and produces a single output y_i. The $(k \times n)$ input matrix is denoted by X and the $(1 \times n)$ output vector is denoted by Y for all n farms where $n = 150$. The technical efficiency can be estimated solving the following linear programming (LP) based DEA model:

$$\begin{aligned} &\underset{\varphi_i^{I,CRS},\omega}{Minimize} && \varphi_i^{I,CRS} \\ &subject\ to && -y_i + Y\omega \geq 0 \\ & && \varphi_i^{I,CRS} x_i - X\omega \geq 0 \\ & && \omega \geq 0 \end{aligned} \tag{6}$$

The scalar, $\varphi_i^{I,CRS}$ $\left(\varphi_i^{I,CRS} \leq 1\right)$, is the technical efficiency score for the i-th farm. The variable returns to scale (VRS) DEA frontier can be formulated by including the convexity constraint, $\Omega'\omega = 1$, in (3), where Ω is an $(n \times 1)$ vector of ones.

A measure of scale efficiency can be obtained as $SE_i^I = \left(\varphi_i^{I,CRS} / \varphi_i^{I,VRS}\right)$, where $\varphi_i^{I,VRS}$ is the measure of efficiency under the setup of VRS DEA. Thus $SE = 1$ implies scale efficiency and $SE < 1$ implies scale inefficiency. Scale inefficiency arises because of the presence of either decreasing (DRS) or increasing (IRS) returns to scale.

In the DEA method, efficiency estimates for each farm are obtained first. Then these are regressed on the factors, such as microcredit, to find their effects on efficiency performance.

5.3. Propensity Score Matching (PSM) Technique

We also use what has come to be known as microcredit impact assessment. Impact assessment requires a group affected by the programme (such as microcredit) intervention, and a control group not receiving microcredit to compare the outcomes. Then, the difference between the two groups is defined as the impact of the programme. Using PSM techniques, the average income of individuals that received microcredit to that of control groups can be compared. The methodology can be described below.

Evaluation studies attempt to estimate the mean effect of participating in a programme (treatment). This requires making an inference about the outcome that would have been observed for the treated ('treatment group') if they had not been treated ('control group'). The key advantage of experimental studies (over non-experimental methods) is the ability to generate a control group that has the same distribution of characteristics as the treatment group. In this case, the treatment effect can be calculated as the difference of mean outcomes. In non-experimental studies on the other hand, subjects usually self-select into treatment groups. Treated and controls differ with respect to their participation status but also with respect to many other characteristics. Calculating the treatment effect as the difference of mean outcomes between the two groups would yield biased results (selection bias).

Matching has become a popular approach to estimate causal treatment effects. It is widely applied when evaluating labour market policies (Heckman *et al.*, 1997 and 1998; Dehejia and Wahba, 1999), but empirical examples can be found in very diverse fields of study. It applies for all situations where one has a treatment, a group of treated individuals and a group of untreated individuals. The nature of treatment may be very diverse. For example, Perkins *et al*. (2000) discussed the usage of matching in pharmacoepidemiologic research. Hitt and Frei (2002) analysed the effect of online banking on the profitability of customers. Davies and Kim (2003) compared the effect on the percentage bid–ask spread of Canadian firms being interlisted on a US Exchange, whereas Brand and Halaby (2006) analysed the effect of elite college attendance on career outcomes. Ham *et al*. (2004) studied the effect of a migration decision on the wage growth of young men. Bryson *et al*. (2002) analysed the effect of union membership on wages of employees.

Every microeconometric evaluation study has to overcome the fundamental evaluation problem and address the possible occurrence of selection bias. The first problem arises because we would like to know the difference between the participants' outcome with and without treatment. Clearly, we cannot observe both outcomes for the same individual at the same time. Taking the mean outcome of non-participants as an approximation is not advisable, since participants and non-participants usually differ even in the absence of treatment. This problem is known as selection bias and a good example is the case where high-skilled individuals have a higher probability of entering a training programme and also have a higher probability of finding a job. The matching approach is one possible solution to the selection problem. It originated from the statistical literature and shows a close link to the experimental context. Its basic idea is to find in a large group of non-participants who are similar to the participants in all relevant pretreatment characteristics X. That being done, differences in outcomes of this well selected and thus adequate control group and of participants can be attributed to the programme. The underlying identifying assumption is known as unconfoundedness, selection on observables or conditional independence. It should be clear that matching is no 'magic bullet' that will solve the evaluation problem in any case. It should only be applied if the underlying identifying assumption can be credibly invoked based on the informational richness of the data and a detailed understanding of the institutional set-up by which selection into treatment takes place (Blundell *et al*., 2005).

The key advantage of matching (over standard regression methods) is that it is less demanding with respect to the modelling assumptions. Specifically, matching does not require functional form assumptions for the outcome equation (it is non-parametric). Further, with matching, there is no need for the assumption of constant additive treatment effects across individuals. Instead, the individual causal effects are unrestricted and individual effect heterogeneity in the population is permitted.

Since conditioning on all relevant covariates is limited in the case of a high dimensional vector X ('curse of dimensionality'), Rosenbaum and Rubin (1983b) suggested the use of so-called balancing scores $b(X)$, i.e. functions of the relevant observed covariates X such that the conditional distribution of X given $b(X)$ is independent of assignment into treatment. One possible balancing score is the propensity score, i.e. the probability of participating in a programme given observed characteristics X. Matching procedures based on this balancing score are known as propensity score matching (PSM).

Let Y_1 be the outcome that would result if an individual receives microcredit and Y_0 the outcome that would result if the same individual does not receive microcredit. Let D = $\{0, 1\}$ denote the binary indicator of microcredit (D = 1 if microcredit, 0 otherwise). For a given individual i, the observed household income is then $Y_i = Y_{0i} + D_i\,(Y_{1i} - Y_{0i})$.

Following Heckman *et al.* (1997 and 1998) and Sianesi (2001), we can attempt to identify the effects of microcredit given below:

a) The average treatment effect: $E(Y_1 - Y_0)$ is the average income difference between the two groups.

b) The average treatment effect on the treated is $E(Y_1 - Y_0 \mid D=1)$. This parameter is the one receiving most attention in the evaluation literature and measures the average income difference between the income that the entrepreneurs who received microcredit earned and the income that they would get if they had not received credit.

c) The average treatment effect on the non-treated: $E(Y_1 - Y_0 \mid D=0)$ is the average income difference between the potential or expected income that the entrepreneurs who did not receive microcredit ($D=0$) would get if they had $(E\,(Y_1))$ and the real income that they earned (Y_0).

Matching is a widely-used non-experimental method of evaluation that can be used to estimate the average effect of a particular programme.[4] This method compares the outcomes of programme participants with those of matched non-participants, where matches are chosen on the basis of similarity in observed characteristics. Suppose there are two groups of farmers indexed by participation status $P = 0/1$, where 1 (0) indicates farms that did (not) participate in a programme. Denote by Y_1 the outcome (performance of farm) conditional on participation ($P = 1$) and by Y_0 the outcome conditional on non-participation ($P = 0$).

The most common evaluation parameter of interest is the mean impact of treatment on the treated, $ATT = E(Y_1 - Y_0 \mid p=1) = E[(Y_1 \mid p=1)] - E[Y_0 \mid p=1]$, which answers the following question: 'How much did farms participating in the programme benefit compared to what they would have experienced without participating in the programme?' Data on $E[(Y_1 \mid p=1)]$ are available from the programme participants. An evaluator's 'classic problem' is to find $E[Y_0 \mid p=1]$, since data on non-participants enables one to identify $E[Y_0 \mid p=0]$ only. So the difference between $E[(Y_1 \mid p=1)]$ and $E[Y_0 \mid p=1]$ cannot be observed for the same farm.

[4] A detailed discussion of the matching approach as well as a survey on its applications in labour-market evaluation studies is available in Heckman, LaLonde and Smith (1999), Caliendo (2006) as well as Caliendo and Kopeinig (2007).

The solution advanced by Rubin (1977) is based on the assumption that given a set of observable covariates X, potential (non-treatment) outcomes are independent of the participation status (conditional independence assumption-CIA): $Y_0 \perp S|X$. Hence, after adjusting for observable differences, the mean of the potential outcome is the same for $P = 1$ and $P = 0$; this is $\left[E\left(Y_0|P=1, X\right)=E\left(Y_0|P=0, X\right)\right]$. This permits the use of matched non-participating farms to measure how the group of participating farms would have performed, had they not participated.

6. Empirical Results

6.1. Summary Statistics of Variables Used

Summary statistics are presented in Table 2. The average revenue of farms is BDT 27218.89 and the coefficient of variation is 64.21 which indicates variability in farm revenues and income. For the analysis, five inputs, land, labour, machinery, fertiliser, seed and irrigation, are used to produce the single output is rice. Fertiliser cost represents 44.98 per cent of average total variable cost (ATVC) and the coefficient of variation (C.V.) of 70.20. This indicates variability of fertiliser use among the farmers. This is followed by labour costs. Labour costs represent 22.80 per cent of ATVC and the C.V. is 84.25. This reflects variation of expenditure on labour among farms. Irrigation costs constitute 17.71 per cent of ATVC with C.V. of 84.43. Machinery costs and seed costs represent 8.65 and 5.85 per cent of ATVC with C.V. of 73.21 and 82.43 respectively.

Table 2 also shows that the amount of microcredit received by the farmers is, on an average, BDT 6872.41 with C.V. of 98.88. The average experience and schooling of the sample farmers are about 39 and 5 years respectively. The mean value of the land fragmentation is 0.30 acre.

Output (y) is defined as the market value of the observed rice production during the survey period. It is measured in Bangladesh Taka (BDT). Land (x_1) represents the rental value of land used for production. We took one per cent of the market price of land as rental value. Some researchers used higher values but we chose this lower value in view of very great increases in the price of land in Bangladesh recently. Labour (x_2) includes both family and hired labour and represents the total costs of labour measured at the market price. Machinery (x_3) represents the cost of using machines in farm production. Fertiliser (x_4) includes all organic and inorganic fertiliser and the total cost of fertiliser is measured at market prices. Seed (x_5) includes seed costs in BDT. Irrigation (x_6) is the total irrigation cost for rice production and is estimated from the total rice land irrigated.

6.2. Stochastic Frontier and Inefficiency Effects Model[5]

We now focus on the estimation of technical efficiency performance using the Cobb-Douglas stochastic frontier model and the technical inefficiency effects model. Technical inefficiency is modelled as a function of microcredit and socioeconomic characteristics of experience, education and land fragmentation. We quantify the factors that include microcredit, which affect inefficiency and have some policy implications regarding the increase of productivity

[5] We estimated the frontier models using value terms of the variables because of heterogeneity of units of some of the variables, like irrigation, machinery. Other researchers also used value terms of the variables (such as, Heshmati and Kumbhakar, 1997; Wadud and White, 2000; Neff, Garcia and Nelson, 1993).

of farms, and hence food security through reduction of farm inefficiency. Table 2 gives a summary statistics of variables, which are used in the models applied in this research.

Table 2

Summary Statistics of Variables (n = 682)

	Mean	Coefficient of Variation	Minimum	Maximum
Revenue	27218.89	64.21	2000	92250
Land	7634.66	86.18	400	36000
Labour	4025.04	84.25	79	20256
Machinery	1527.65	73.21	100	8400
Fertiliser	7939.35	70.20	520	29970
Seed	1033.30	82.43	24	7740
Irrigation	3126.50	84.43	100	19280
Amount of Credit Taken	6872.41	98.88	0	45000
Years of Experience	39.10	26.70	18	73
Years of Education	5.47	76.46	0	16
Land Fragmentation	0.30	73.39	0.08	1.69

The maximum likelihood estimates of the parameters of the Cobb-Douglas frontier models for the whole sample which includes both microcredit receivers and non-receivers are presented in Table 3. The signs of the β-coefficients are all positive and significant as expected. The highest elasticity of output is for fertiliser which indicates that fertiliser is the dominant factor of production. Machinery is the next important input followed by land. Labour, irrigation and seed have relatively small effects. The returns to scale of 0.8633 indicating slightly decreasing returns to scale.

We calculate the overall technical inefficiency effects in the stochastic frontier with respect to the coefficients of the parameters associated with σ_u^2 and γ reported in the middle section of Table 3. The coefficients of the parameters, σ_u^2 and γ, are estimated to be 0.0958 and 0.7782 respectively and both are significant. These indicate that the technical inefficiency effects are a significant component of the total variability of output. This means that there exists substantial amount of inefficiency in farm production. Therefore, there is room for improvement of farm output and food security through decreasing inefficiency of farms.

Table 3
Results of the Stochastic Frontier Model (N=682)

	Parameter	Coefficients	t-ratios
Constant	β_0	3.2874	28.2894
Land	β_1	0.1490	7.6726
Labour	β_2	0.1098	4.8439
Machinery	β_3	0.1852	5.7833
Fertiliser	β_4	0.2676	9.9439
Seed	β_5	0.0460	1.9263
Irrigation	β_6	0.1057	4.4745
Variance Parameters			
Sigma-squared	$\sigma^2 = \sigma_\xi^2 + \sigma_\zeta^2$	0.0958	11.8545
Gamma	$\gamma = \left(\sigma_\zeta^2 / \sigma^2\right)$	0.7782	19.4612
	σ_ξ^2	0.0212	
	σ_ζ^2	0.0746	
Log likelihood Value			76.3301
Inefficiency Effects Model: Factors Affecting Inefficiency			
Constant	δ_0	.19259	12.2124
Microcredit	δ_1	-.4130E-6	-.78983
Experience	δ_2	-.8509E-3	-2.4786
Education Level	δ_3	-.0014415	-1.6665
Land Fragmentation[6]	δ_4	.10974	6.8147
R-Squared		.068286	
DW-statistic		1.5061	

[6] Square terms of land fragmentation were included in this and other models and the models were re-estimated, but results remained unchanged in terms of signs and significance. Therefore we did not report those results.

Differences in inefficiencies are likely to be due to factors that vary among farmers. An analysis of inefficiency by microcredit, experience and education of farmers, and land fragmentation provides some explanation of these factors which affect efficiency performances. Inefficiency is hypothesised to be determined by microcredit, experience and education of farmers, and land fragmentation, that is:

$$IE_i = \delta_0 + \delta_1 z_{1i} + \delta_2 z_{2i} + \delta_3 z_{3i} + \delta_4 z_{4i} + w_i$$

where IE denotes farm inefficiency, z_i's are microcredit, experience and education of farmers, and land fragmentation. w_i is a stochastic random error assumed to be normally distributed. As IE is a measure of inefficiency, the dependent variable with a positive (negative) coefficient will have a negative (positive) effect on the level of efficiency.

We now turn to explain results of the inefficiency effects model by the farm-specific microcredit, socioeconomic, and land fragmentation variables. Results are shown in the lower section of Table 3. The coefficient for microcredit, experience and education are all negative as expected.[7] This implies that microcredit helps reduce inefficiency in agricultural farm production. Further, this indicates that farmers with higher experience and greater years of schooling have more efficiency performance than those with fewer years of schooling experience. Thus farmers with more education, experience and microcredit are capable of utilising their agricultural inputs in an efficient way that in turns increase agricultural farm production and income, and hence contribute to improvement of food security.

The estimated coefficients for land fragmentation are positive which shows that increase in land fragmentation causes inefficiency in farm production. This is perhaps because of land fragmentation, marginal and small farmers can neither better apply new technologies like tractors and nor manage irrigation on their land.

Table 4 provides results of the stochastic frontier model, variance parameters and inefficiency effects model of microcredit receivers of 450 farmers. Results show that all the β coefficients are positive as expected and five out of six are significant. Here also fertiliser is found to be the dominant factor followed by machinery and land. Irrigation has relatively smaller effect. The returns to scale of 0.8415 implies that farms are operating at below the optimal levels.

Table 4 also shows that the coefficients of the variance parameters of σ_u^2 and γ, are estimated to be 0.0971 and 0.7391 respectively and both are significant. These imply that inefficiency part of the composite error term is significant in total variability of output. Therefore, there is scope for enhancement of farm output and food security through reduction in farm.

Results of the inefficiency effects model for microcredit receivers are given in the lower section of Table 4. We found that the coefficient for microcredit, experience and education are all negative which is expected. This means that these variables help utilise their agricultural inputs properly, given the state of technology. This again contributes to the increase in agricultural farm production and income, and food security.

[7] The estimated coefficient for microcredit is not statistically significant as perhaps the proportion of microcredit to total cost of farms was small.

Table 4
Stochastic Frontier Results for Microcredit Receivers (n=450)

	Parameter	Coefficient	t-ratio
Constant	β_0	3.4665	23.9779
Land	β_1	0.1535	5.9247
Labour	β_2	0.0936	3.2611
Machinery	β_3	0.1562	3.7706
Fertiliser	β_4	0.2972	8.3763
Seed	β_5	0.1017	3.3674
Irrigation	β_6	0.0393	1.2794
Variance Parameters			
Sigma-squared	$\sigma^2 = \sigma_\xi^2 + \sigma_\zeta^2$	0.0971	9.2753
Gamma	$\gamma = \left(\sigma_\zeta^2 / \sigma^2\right)$	0.7391	12.7858
	σ_ξ^2	0.0253	
	σ_ζ^2	0.0718	
log likelihood Value			35.0439
Inefficiency Effects Model for Microcredit Receivers (n = 450)			
Constant	δ_0	.18448	9.6800
Credit	δ_1	-.1380E-5	-1.8817
Experience	δ_2	-.5557E-3	-1.3719
Education Level	δ_3	-.5126E-3	-.48307
Land Fragmentation	δ_4	.11066	5.5847
R-Squared		.072546	
DW-statistic		1.6084	

We also derive results of the stochastic frontier, variance parameter and inefficiency effects models of the farmers who did not receive microcredit. Results are given in Table 5. Results reveal that all the β coefficient except that for seed are positive and significant. The coefficient for seed is negative but insignificant. Unlike microcredit receiving farms, here irrigation stands as the dominant factor followed by machinery and fertiliser. The returns to scale of these farms is 0.9203 which implies that farms are operating at below the optimal levels.

Table 5

Stochastic Frontier Results for Microcredit Non-receivers (n=232)

	Parameter	Coefficient	t-ratio
Constant	β_0	2.8762	16.3434
Land	β_1	0.1331	5.0301
Labour	β_2	0.1429	4.1846
Machinery	β_3	0.2265	4.6271
Fertiliser	β_4	0.2041	5.3119
Seed	β_5	-0.0277	-0.7865
Irrigation	β_6	0.2414	6.4211
Variance Parameters			
Sigma-squared	$\sigma^2 = \sigma_\xi^2 + \sigma_\zeta^2$	0.0883	7.6489
Gamma	$\gamma = \left(\sigma_\zeta^2 / \sigma^2\right)$	0.9103	25.7241
	σ_ξ^2	0.0079	
	σ_ζ^2	0.0804	
log likelihood Value			63.6853

The coefficients of the variance parameters of microcredit non-receiving farms are positive and significant implying that these are significant components in total variability of output.[8]

6.3. Levels of Farm-specific Efficiency Performance

We present frequency distribution of the estimates of farm-specific efficiency performance and their summary statistics for all farmers, farmers who did receive microcredit and who did not in Table 6, 7 and 8 respectively.

Table 6 shows that the estimated farm-specific technical efficiencies show substantial variability, ranging between 35-97 per cent with a mean value of 81.81 per cent and a standard deviation of 9.47 per cent for microcredit receiving and non-receiving farms together. The associated histogram of the efficiency index is presented in Figure 2.

The majority of farms, 56.01 per cent are 80-90 per cent technically efficient; 20.97 per cent of farms are between 70-80 per cent technically efficient; 11.58 per cent of farms are between 90-100 per cent technically efficient, 6.89 per cent of farms are between 60-70 per cent technically efficient; 3.52 per cent of farms are between 50-60 per cent technical efficient; only about one per cent of farms are between 1-50 per cent technical efficient; however no farm is fully efficient. Therefore it appears that there is considerable room for

[8] As these farmers did not receive microcredit, results of inefficiency effects model are not produced.

improvement in productivity through increased technical efficiency. More than 18 per cent production cost could be reduced if farms could operate at full efficiency levels, given the state of technology.

Table 6

Frequency Distribution of Efficiency Index (n = 682)

Efficiency Index	Number of Farms	Percentage of Farms	Cumulative Frequency
0 - 50	7	1.03	7
50 - 60	24	3.52	31
60 - 70	47	6.89	78
70 - 80	143	20.97	221
80 - 90	382	56.01	603
90 - 100	79	11.58	682
Mean Efficiency	**Standard Deviation of Efficiency**	**Maximum Efficiency**	**Minimum Efficiency**
81.81	9.47	97	35

We find in Table 7 that microcredit receivers' estimated farm-specific technical efficiencies vary from 37-96 per cent with a mean value of 82 per cent and a standard deviation of 8.84 per cent. The associated histogram of the efficiency index is presented in Figure 3.

Figure 2

Frequency Distribution of Efficiency Index of Microcredit Receivers

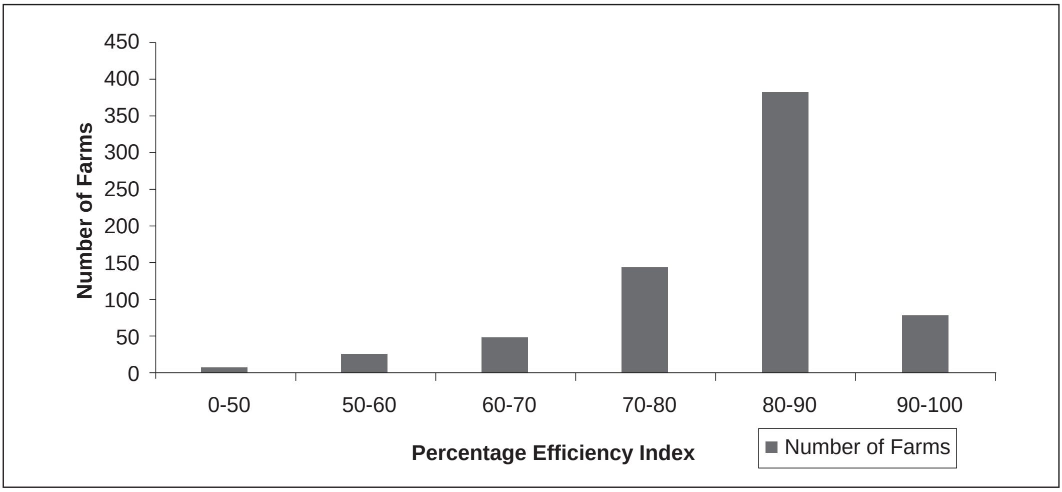


Table 7

Frequency Distribution of Efficiency Index of Microcredit Receiver Farms (n = 450)

Efficiency Index	Number of Farms	Percentage of Farms	Cumulative of Farms
0 - 50	4	0.89	4
50 - 60	10	2.22	14
60 - 70	32	7.11	46
70 - 80	98	21.78	144
80 - 90	265	58.89	409
90 - 100	41	9.11	450
Mean Efficiency	**Standard Deviation of Efficiency**	**Maximum Efficiency**	**Minimum Efficiency**
82.10	8.84	96	37

Results reveal that 58.89 per cent, that is, the majority of farms are 80-90 per cent technically efficient; and 21.78 per cent of farms are between 70-80 per cent technically efficient. Less than one per cent of farms are between 1-50 per cent technical efficient with no farm fully efficient. Therefore it appears that there is considerable scope for improvement in productivity through increased technical efficiency. About 18 per cent production cost could be reduced if farms could operate at full efficiency levels, given the state of technology.

Figure 3

Frequency Distribution of Efficiency Index of Microcredit Receivers

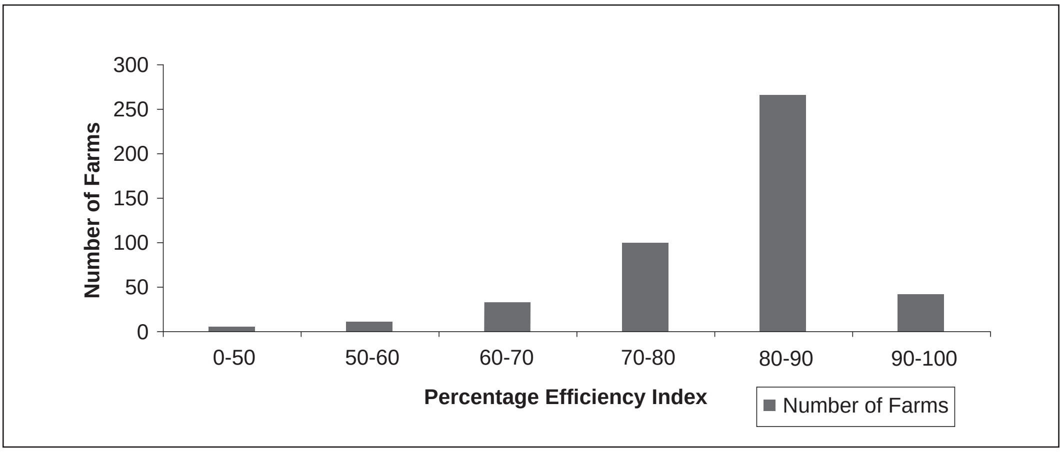


Table 7 shows that the variability of the estimated farm-specific technical efficiencies ranges 40-98 per cent of microcredit non-receiving farms. The average efficiency performance of these farms is about 81 per cent with a standard deviation of 11.56 per cent.

An analysis of efficiency shows that the majority of farms, 37.93 per cent are 80-90 per cent technically efficient; and 33.71 per cent of farms are between 90-100 per cent technically efficient. More than two per cent of farms are between 1-50 per cent technical efficient. No farm is found to be fully efficient. Therefore it appears that there is considerable scope for improvement in productivity through increased technical efficiency. The histogram of the efficiency index is presented in Figure 4.

Table 8

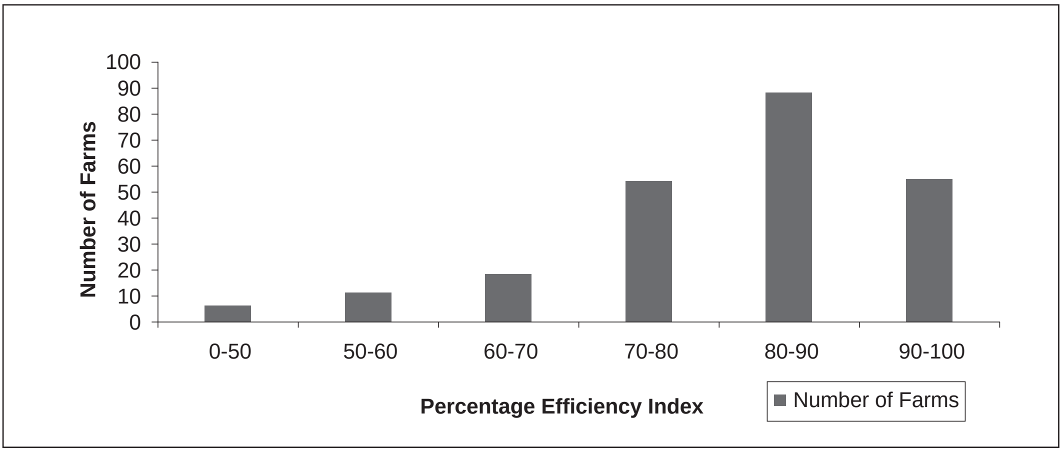
Frequency Distribution of Efficiency Index of Microcredit Non-receiving Farms (n = 232)

Efficiency Index	Number of Farms	Percentage of Farms	Cumulative of Farms
0 - 50	6	2.59	6
50 - 60	11	4.74	17
60 - 70	18	7.76	35
70 - 80	54	23.28	89
80 - 90	88	37.93	177
90 - 100	55	23.71	232
Mean Efficiency	**Standard Deviation of Efficiency**	**Maximum Efficiency**	**Minimum Efficiency**
81.39	11.56	98.00	40

If we look at the efficiency performance of microcredit receiving and non-receiving farms in Table 7 and 8, it is evident that the average efficiency performance of microcredit receiving forms is about one per cent higher than microcredit non-receiving farms. This difference in efficiency between microcredit receiving and non-receiving farms seems to be small. This is perhaps because that microcredit received by the farmers is a small part of their total cost of production. The variability of farm-specific efficiency performance among farms is

Figure 4

Frequency Distribution of Efficiency Index of Microcredit Non-receivers



higher in the later farms than the former. This can be explained as the contribution of the microcredit. Thus we can conclude that microcredit can reduce inefficiency, and hence increase efficiency performance which could lead to enhancement of farm output and food security.

6.4. Results of DEA Model

The constant returns to scale (CRS) and variable returns to scale (VRS) DEA technical efficiency (TE) estimates derived from the DEA are regressed on farm-specific explanatory variables of microcredit, experience, years of schooling of the farmers and land fragmentation to identify and quantify possible factors associated with inefficiency. The effects of these explanatory variables on the technical inefficiency of farms are investigated. We specify the following regression to conduct the analysis:

$$IE_i = \delta_1 x_{1i} + \delta_2 x_{2i} + \delta_3 x_{3i} + \delta_4 x_{4i} + w_i$$

if $(\delta_1 x_{1i} + \delta_2 x_{2i} + \delta_3 x_{3i} + \delta_4 x_{4i} + w_i) > 0$, i.e., inefficiency is not zero,

and $IE_i = 0$ otherwise, i.e., inefficiency is zero

Results are presented in Table 9 and 10. The CRS technical inefficiency (CRS TI) and VRS technical inefficiency (VRS TI) are corresponding efficiencies subtracted from 100.

Table 9 provides results of inefficiency effects for all farms which include microcredit receivers and microcredit non-receivers while Table 10 gives results of that for microcredit receiving farms. Results from both Table 9 and 10 exhibit that the signs of the estimated coefficients associated with microcredit, experience and years of schooling VRS TI are negative for specification which includes all farms and which includes microcredit receivers only. This implies that the farmers with more microcredit, more farming experience and levels of education are more efficient in their farming activities. But coefficients associated with CRS TI exhibit positive signs which are not expected. This is perhaps due to the imposition of constant returns to scale assumption. Results show that technical inefficiency effects are higher for farmers with smaller land size because farmers with smaller land size can not operate modern equipment and manage irrigation more effectively on their small plots. Again this accords with Coelli and Battese (1996).

Table 9

Results of Inefficiency Effects Model Showing Relationship between Technical Inefficiency and Factors Associated with Inefficiency (n = 682)

CRS Technical Inefficiency			VRS Technical Inefficiency	
Regressor	**Coefficient**	**T-Ratio**	**Coefficient**	**T-Ratio**
Constant	.083921	16.2506	.092155	15.3697
Credit	.6871E-6	4.0125	-.3097E-6	-1.5577
Experience	-.2262E-3	-2.0121	-.5087E-3	-3.8975
Education Level	.8623E-3	3.0442	-.0012121	-3.6856
Land Fragmentation	.037503	7.1120	.014031	2.2917
R-Square[9]	.12239		.041995	
DW-statistic	1.5418		1.5739	

[9] R-Squares in both Table 9 and 10 are estimated to be small. This is perhaps because of the low variation in efficiency performances among farms that is reflected in low values of standard deviations.

Table 10

Results of Inefficiency Effects Model Showing Relationship between Technical Inefficiency and Factors Associated with Inefficiency (n = 450)

CRS Technical Inefficiency			VRS Technical Inefficiency	
Regressor	**Coefficient**	**T-Ratio**	**Coefficient**	**T-Ratio**
Constant	.067937	10.3113	.091391	11.7589
Credit	.1783E-5	7.0306	-.6440E-6	-2.1527
Experience	-.1805E-3	-1.2887	-.4080E-3	-2.4696
Education Level	.8429E-4	.22975	-.0013815	-3.1920
Land Fragmentation	.050876	7.4270	.022279	2.7571
R-Square	.20908		.058049	
DW-statistic	1.7493		1.7128	

Results confirm that microcredit along with farming experience and education contributes to agricultural farm performance which leads to the increase in crop output and output supply. This subsequently helps increase food security. A policy which helps timely and adequate distribution of microcredit could enhance crop yields and hence farm revenues and food security through improvement of farmers' efficiency.

6.5. Results from Logistic Regression and Propensity Scores

Propensity score matching (PSM) technique is used to assess the impact of microcredit. We apply the specification of logistic regression model to obtain propensity score as a function of set of variables of experience and years of schooling of farms, and land fragmentation and farm size of farms. The estimated propensity score abstracts the information of the covariates of participants as x and participant's status on the variable as y. Using the estimated propensity score, we match a participant from the treatment group (microcredit receivers) with a participant from the control group (microcredit non-receivers) to facilitate causal inference so that the treatment group and control group are balanced. This approach significantly reduces the selection bias in observational study (Rosenbaum, 1987 and 2004; Rosenbaum and Rubin, 1985; and Rubin and Thomas, 1992). Ideally, the farmers representing on matched pair are identical to each other except microcredit. As a consequence, this approach isolates the impact idiosyncratic factors have on outcome variables by reducing heterogeneity between microcredit receivers and non-receivers. An important characteristic of this technique is that, after units of the groups are matched, the unmatched comparison units are discarded and not used in estimating the impact.

Different algorithms can be employed to identify matching pairs after the propensity score is estimated (Rubin, 1974). We used the Nearest-Neighbour Algorithm in this study as this is the most applied algorithm. This method matches each treated observation with a controlled observation with the closest propensity score.

Results are reported in Table 10. Results imply that farmers with experience and education do have probability of receiving microcredit, and that farmers with land fragmentation are likely to receive microcredit. Farmers with larger farm size are unlikely to receive microcredit.

Table 11

Logistic Regression for Propensity Score[10] and Programme Effect

Regressor	Coefficient	t-ratio
Experience	.013073	3.1139
Education	.014853	.81103
Land Fragmentation	.11909	.31938
Farm Size	-.033486	-.35956
Goodness of fit		0.65982
Maximised value of the log-likelihood function		-442.7508
Programme Effect		
Mean Income of Matched Treated		18397.40
Mean Income of Matched Controlled		16656.30
Impact of Microcredit Programme		1741.13

Note: Total number of observations is 682; Microcredit receivers and non-receivers are 450 and 232 respectively. Matched treated and controls are 165 and 165 respectively. Factor for the calculation of marginal effects = 0.22943, Pseudo-R-Squared = 0.063410.

Once each treated farmer is matched with a control farmer, the difference between the outcome of the treated farmer and the outcome of the control farmer is calculated. The average effect of treatment on the treated (ATT) is then obtained by averaging these differences. The impacts of the microcredit programme for agriculture are shown at the end of Table 10. The microcredit programme as a whole has a positive impact on the average income of farms. This positive impact means that those receiving microcredit earn, on an average, 9.46 per cent more than those who did not. This definitely contributes to food security.

7. Conclusions

This study aims to assess the impact of microcredit on the performance of agricultural farms and hence food security. We apply the Cobb-Douglas stochastic frontier (SF) model, data envelopment analysis (DEA) method and the propensity score matching (PSM) technique to evaluate the role of microcredit on farm performance, farm productivity and consequent food security. We conduct a field survey in 2009 to collect data.

We first specify the Cobb-Douglas stochastic frontier model to obtain farm-specific efficiency performance along with output elasticity and coefficients of variance parameters. We apply maximum likelihood estimation methodology to estimate the frontier model. The estimates of the output elasticities have the expected signs for all farms together and for microcredit receiving farms. They all are significant. Farms are characterised by slightly decreasing returns to scale. Furthermore, the coefficient of the variance parameters indicates that the technical inefficiency effects are a significant component of the total

[10] The variables which are likely to influence both the treatment and outcome are included in the logistic regression from which we derive the propensity score.

variability of output. This means that there exists substantial amount of inefficiency in farm production. Therefore, there is room for improvement of farm output and food security through decreasing inefficiency of farms.

The technical efficiency performance among the farms ranges from 35 to 97 per cent with a mean of 81.81 per cent for all farms. For farms receiving microcredit, efficiency performance ranges from 37-96 per cent with an average efficiency performance of 82.10 per cent and for farms not receiving microcredit, this performance ranges from 40-98 with a mean of 81.39 per cent. Agricultural efficiency performance of microcredit receiving farms is about one per cent higher than that of microcredit non-receiving farms. This could be interpreted as the positive impact of microcredit on farm performance. Farms could, on an average, reduce their production cost by about 19 per cent and hence increase their output if they could operate at full efficiency levels. This could subsequently contribute to improvement of food supply and security.

We specify the technical inefficiency effects model for both the stochastic frontier model and DEA model. This includes the farm-specific variables – microcredit, experience, education of farmers and land fragmentation. A feature of the inefficiency models is that it includes microcredit to examine its effects on farm efficiency. The results of the analysis of inefficiency by these factors show that microcredit helps reduce inefficiency in farms. Experience and education of farmers also contribute to improvement of efficiency performance. Experienced and educated farmers with microcredit are more likely to operate farming activities more efficiently.

Results of the propensity score matching (PSM) technique reveal that microcredit contributes to output and income generation. This generated income would, no doubt, help poverty reduction and ensure food security of marginal and small farms in Bangladesh.

Based on the results of this study, we conclude that policies which extend microcredit and ensure fair, timely and low-cost delivery of microcredit to marginal and small farmers could lead to reduction of agricultural farm inefficiency and hence lead to improvement of performance of farms. This could enhance farm output and welfare, help reduce poverty and improve food security.

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Appendices

Appendix 1
Name of Villages Surveyed and Number of Households in Rangpur District

Serial No.	Name of Villages	Number of Households		
		Microcredit Receiver	Microcredit Non-receiver	Total
1	Bhabanipur	29	10	39
2	Dublaghari	23	10	33
3	Sabdin	20	21	41
4	Narayanpur	25	09	34
5	Basudevpur	14	10	24
Total		111	60	171

Appendix 2

Name of Villages Surveyed and Number of Households in Dinajpur District

Serial No.	Name of Villages	Number of Households		
		Microcredit Receiver	Microcredit Non-receiver	Total
1	Singra	5	1	6
2	South Devipur	8	1	9
3	Srichandrapur	10	6	16
4	Abdullahpur	9	4	13
5	Kulanandapur	7	3	10
6	Baratipur	8	5	13
7	Raghunathpur	7	1	8
8	Vathsala	12	13	25
9	Shampur	5	8	13
10	Rameshsorpur	9	2	11
11	Kashigari	7	2	9
12	Nurpur	8	3	11
13	Belwas	2	0	2
14	Balgari	1	1	2
15	Maglishpur	3	0	3
16	Ohiohra	1	2	3
17	Kumuria	1	1	2
18	Maricha	0	2	2
19	Rampur	1	1	2
20	Krishnarampur	1	1	2
21	Chowgacha	1	0	1
22	Marupara	1	0	1
23	Shekhalipara	0	1	1
24	Satpara	0	1	1
25	Dangapara	0	1	1
26	Majhiyan	1	0	1
27	Bamongara	1	0	1
28	Binnagari	0	1	1
29	Amra	1	0	1
Total		110	61	171

Appendix 3

Name of Villages Surveyed and Number of Households in Rajshahi District

Serial No.	Name of Villages	Number of Households		
		Microcredit Receiver	Microcredit Non-receiver	Total
1	Mirzapur	13	0	13
2	Matikata	11	0	11
3	Batupara	12	3	15
4	Harifahla	15	0	15
5	Chandpur	11	0	11
6	Nandanhat	13	0	13
7	Dhurail W. para	2	5	7
8	Bidirpur	1	3	4
9	Hariharpur	9	4	13
10	Dashopara	1	2	3
11	Basantakeda	1	5	6
12	Kaligram	2	6	8
13	Moughachi	20	3	23
14	Dhurail S. Para	0	7	7
15	Boritha	0	8	8
16	Baksoil	0	5	5
17	Ilamatpur	0	3	3
18	Suipara	0	5	5
Total		111	59	170

Appendix 4

Name of Villages Surveyed and Number of Households of Joypurhat Sadar Upazilla in Joypurhat District of Greater Bogra

Serial No.	Name of Villages	Number of Households		
		Microcredit Receiver	Microcredit Non-receiver	Total
1	Baniapara	2	2	4
2	Chakdadra Fakirpara	2	0	2
3	Chakvarunia	2	5	7
4	Dadra Chandi Gram	1	0	1
5	Dharki	5	1	6
6	Dhogachi	1	0	1
7	East Sundurpur	1	0	1
8	Gobindapur	1	0	1
9	Hanail	1	4	5
10	Helkunda	2	0	2
11	Hichmi	8	0	8
12	Isahakpur	2	0	2
13	Zidarpur	2	0	2
14	Kadoa	5	0	5
15	Kendul Mondol Para	2	1	3
16	Khaspainda	0	2	2
17	Komorgram	0	1	1
18	Malaypur	3	0	3
19	Muralipara	1	0	1
20	Narayanpara	3	0	3
21	Nurpur	0	1	1
22	Pachorchak	0	1	1
23	Paikor	3	1	4
24	Pali Chak Jogodishpur	1	0	1
25	Palibari	1	0	1
26	Parbotipur	1	0	1
27	Pathuria Master Para	2	0	1
28	Pechulia	2	0	2
29	Sogunapara	0	1	1
30	Sonar Para	2	0	2
31	Tu Para	4	0	4
32	Vadsha Hajipara	1	0	1
33	West Pali	1	0	1
Total		62	20	82

Appendix 5
Name of Villages Surveyed and Number of Households of Kalai Upazilla in Joypurhat District of Greater Bogra

Serial No.	Name of Villages	Number of Households		
		Microcredit Receiver	Microcredit Non-receivers	Total
1	Aklarpara Gopinathpur	1	0	1
2	Atahar	1	0	1
3	Akdala	1	0	1
4	Aura	1	1	2
5	Balakur	0	1	1
6	Bamongram	1	0	1
7	Bandhigi	1	0	1
8	Begungram	0	1	1
9	Bhabki	1	0	1
10	Bishnopur	1	0	1
11	Chingrapara	1	0	1
12	Dhap	1	0	1
13	Dingrapara	0	1	1
14	Durgapur	1	0	1
15	Garail	2	0	2
16	Ghaturia	1	0	1
17	Hajipur	5	0	5
18	Haruja	0	1	1
19	Indahar	0	1	1
20	Jinot	0	1	1
21	Joypur Kahchi	0	1	1
22	Kalai East Para	0	2	2
23	Kathail	1	0	1
24	Kharpa	1	0	1
25	Moheshpur	1	0	1
26	Mulgram East Para	0	1	1
27	Nanahar	2	0	2
28	Naopata	0	1	1
29	Naotika	0	1	1
30	Nosirpur	0	1	1
31	Punot Maheshshor Para	1	0	1
32	Satar	0	1	1
33	Shikta East Para	0	1	1
34	Sorail	1	0	1
35	Talora Baiguni	0	1	1
Total		26	17	43

Appendix 6

Name of Villages Surveyed and Number of Households of Khetlal Upazilla in Joypurhat District of Greater Bogra

Serial No.	Name of Villages	Number of Households		
		Microcredit Receiver	Microcredit Non-receivers	Total
1	Alampur	2	1	3
2	Amnia	1	0	1
3	Atimukul	1	0	1
4	Damgor	1	0	1
5	Daulotpur	1	0	1
6	Dashra	0	1	1
7	Dhotwa Pukur	1	0	1
8	Fakirpara	4	0	4
9	Golahar	1	0	1
10	Hinda	0	3	3
11	Ikorgara	1	2	3
12	Kortowapara	0	1	1
13	Majhiasthal	1	0	1
14	Minigari	6	0	6
15	Nasirpur	1	0	1
16	Poulanja	2	0	2
17	Sagaram Pur	1	0	1
18	Shialpara	1	0	1
19	Shishi Nazirpara	1	0	1
20	Shurjaban	1	0	1
21	Shyampur	1	0	1
22	Sorail	2	3	5
23	Sultanpur	0	1	1
24	Talkan	0	2	2
25	Tilabdul	0	1	1
Total		30	15	45

Appendix 7

Number of Farm Households According to Farm Size Distribution

Farm Size (including sharecropping land)	Number of Farms	Percentage of Farms	Cumulative Percentage of Farms
0-0.5	155	22.73	22.73
0.5 - 1.00	266	39.00	61.73
1.00 - 1.50	102	14.96	76.69
1.50 - 2.00	70	10.26	86.95
2.00 - above	89	13.05	100.00
Total	682	100.00	

Appendix 8

Number of Farms According to Microcredit Distribution

Microcredit Received	Number of Microcredit Receivers	Percentage of Farms	Cumulative Percentage of Farms
0-10000	248	55.11	55.11
10000-20000	182	40.44	95.55
20000 above	20	4.44	100.00
Total	450	100.00	

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