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Technical Efficiency Analysis of PRIME Branches in Monga Areas of Bangladesh: An Application of Data Envelopment Analysis

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The paper is an outcome of an InM research study entitled "Programmed Initiatives for Monga Eradication (PRIME)". The author is grateful to DFID's PROSPER (Promoting Financial Services for Poverty Reduction) Program for providing funds for the study. However, the views expressed in this paper are entirely of the author and do not necessarily reflect the views of InM, DFID or any other affiliated organizations.

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Abstract

This paper evaluates the efficiency of Programmed Initiatives for *Monga* Eradication (PRIME) branches by using non-parametric Data Envelopment Analysis (DEA) in five districts of North-West region of Bangladesh. The production function approach is used for the assessment of efficiency scores of 149 branches under both constant and variable returns to scale. The results of the study revealed that there were considerable inefficiencies among PRIME branches for the year of 2010 to 2012. In addition, a second stage Tobit regression shows that the variation is also related to branch-specific attributes such as branch age, PRIME to total member ratio, borrower per staff, and location. Since PRIME is an ultra-poor program, it is suggested that achieving higher efficiency might take longer time as old branches were more efficient than new ones. It is, therefore, also suggested that by employing more skilled staff, borrower per staff as well as branches efficiency will be increased in the study areas. However, Kurigram was less scale efficient and Nilphamari was more technically efficient in contrast to Rangpur district. This result implies that for expanding PRIME branches in future, selection of appropriate location will help to achieve higher efficiency.

Key Words: Efficiency, Microfinance, PRIME branches, DEA, Tobit model

Technical Efficiency Analysis of PRIME Branches in Monga Areas of Bangladesh: An Application of Data Envelopment Analysis*

Farhana Nargis[a]

1. Introduction

The rural poor households in North-Western Bangladesh have been suffering from food crisis and seasonal hunger during late September to mid-November *(Bangla months of Bhadra-Kartik)* every year. Life gets harder during these months because they face famine, many cannot afford to eat three times a day, often even struggling to have one decent meal. Many households, more particularly poor people, face extreme hardship because most of them rely on farm work. But, at this time they are jobless, waiting for the harvest of transplanted rice in December. By the time the famine season commences, they have consumed all of their stored food and do not have any opportunities for work; this causes the seasonal hunger. This situation is more severe for the ultra-poor households due to their greater dependency on wage labor or low-income activities. However, limited number of manufacturing jobs and limited scope for industrialization narrowed down their income earning opportunities to only agriculture. Besides, this region is primarily a flat land with major river systems and floods are very common which makes their lives more difficult. This situation is commonly known as *'monga'*, which is not a crisis of recent years but is a century old problem.

In this background, Palli Karma Sahayak Foundation (PKSF), a wholesale lending agency as well as a central institution committed to poverty alleviation, has undertaken *monga* mitigation program, commonly known as Programmed Initiatives for *Monga* Eradication (PRIME). The PRIME project was established in 2006. It provides financial services to the ultra-poor households in five districts - namely, Lalmonirhat, Kurigram, Gaibandha, Nilphamari and Rangpur of North-West region of Bangladesh. PKSF uses 16 Partner Organizations (POs) to implement PRIME in North-Western Bangladesh, selected on the basis of commitment and working experience with the ultra-poor, track record of working with PKSF, institutional capacity to absorb shocks and deliver flexible financial services, training and other support to the ultra-poor. These POs have around 230 branches operating in the five stated districts, and most of them operate some other micro credit programs along with PRIME.

The short and long term objectives of PRIME were helping people to avoid seasonal hunger and creating diversified income sources respectively. Financial and non-financial products like emergency seasonal loan and food-for-work were put into practice to meet the short objective.

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Long-term incentives include flexible microcredit, micro savings, and training on income and employment generating activities for the targeted members. Besides this, PRIME also provides health services and medicines to its members. The PRIME branches offer services to the ultra-poor in the remote areas where these branches face lower revenues from loan service charges and higher operating costs[1]. However, over the last four years the PRIME branches have experienced high revenue growth in comparison to the growth in expenditure which resulted in a viable financial scenario for the PRIME branches.

The success of PRIME will certainly provide the world with a unique model of integrated intervention that can help the ultra-poor walk out of seasonal hunger without sacrificing program sustainability. Microcredit, after its pioneering inception in the mid-1970s, has undergone numerous replication, experimentation, evaluation as well as criticism. There have been several research studies to evaluate the impact of PRIME intervention on *monga* mitigation. From the user (demand-side) perspective, studies have shown expansion in consumption, income, self-employment (see, for instance, Khalily *et al.*, 2010; Khandker and Mahmud, 2010; Rabbani *et al.*, 2011). The success stories of demand-side encouraged PKSF to extend the PRIME project to southern Bangladesh. On the other hand, it is yet to be established whether the program is efficient, sustainable and replicable from the institutional (supply-side) perspective. To some extent the literature already establishes the negative relationship between serving the ultra-poor with credit and program sustainability, as serving the poor has high transaction and information cost (for instance, see Cull *et al.*, 2007). However, research on supply-side issues of microfinance program in Bangladesh has been quite limited. A few studies have been done on efficiency of microfinance institutions (MFIs), and those were constrained by the absence of reliable and extensive datasets. This present study broadly covered efficiency of PRIME branches in selected areas of Bangladesh.

The objectives of this research are two fold. First, we evaluate technical efficiency - pure technical and scale efficiency - using the DEA model. Second, we use- the Tobit model to identify statistically significant determinants of technical efficiency.

2. Concepts of Technical and Scale Efficiency

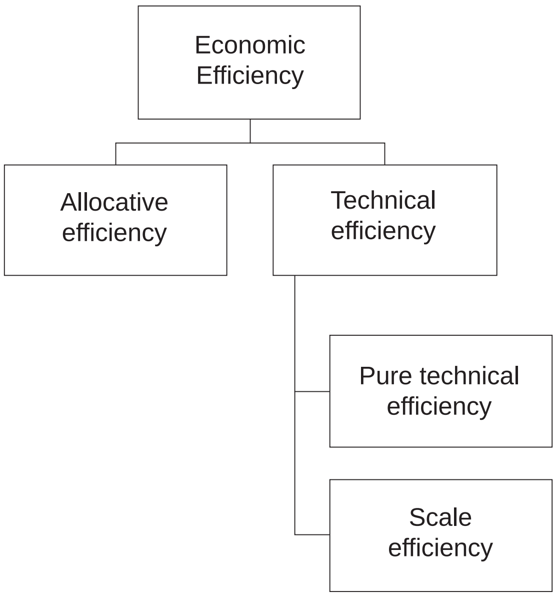
Efficiency or performance analysis is a relative concept (Coelli *et al.*, 1998). It relates to production analysis and measures production in a ratio form. Efficiency measurement is an ex-post evaluation, which can be applied to micro level of decision making units (DMUs) or private firms, non-profit organizations as well as to compare the performance of industrial, regional, and national levels (Cooper *et al.*, 2006). Efficiency in microfinance institutions refers to efficient use of resources such as the subsidies, human capital and assets owned by microfinance institutions to produce output measured in terms of loan portfolio and number of active borrowers (ILO, 2007).

For multi output-input firms such as banks, financial institutions, MFIs, efficiency can be viewed

[1] The interest rate on PRIME loans are lower than more regular loan products

as either using production approach or intermediation approach depending on the choice of inputs and output variables (Kipesha, 2012; Sealey and Lindley, 1977; Berger and Humphery, 1997). The production approach views microfinance institutions as producers of services for poor clients and assumes that the services are produced by utilizing physical resources of the institution such as capital, labour, assets and operating costs to produce loans, revenues, and savings (Nghiem *et al.*, 2006; Bassem, 2008; Haq *et al.*, 2010; Gutierrez-Nieto *et al.*, 2009; Soteriou and Zenios, 1999; Vassiloglou and Giokas, 1990). On the other hand, under the financial intermediation approach, deposits are treated as inputs with a surplus generation as output (Berger and Mester, 1997; Athanassoupoulos, 1997) and financial institutions are considered as institutions transferring resources from savers to investors. Following a range of studies examining efficiency issues in the MFIs, we adopted the production approach for defining variables. As per the production efficiency approach, MFIs have been modeled as multi product firms in this study, each producing two outputs, viz., loan outstanding and savings. The number of employees and fixed asset are considered as inputs.

The following diagram sets out the progression of efficiency measures outlined above.



Technical efficiency relates to the degree to which a firm produces the maximum feasible output from a given bundle of inputs, or uses the minimum feasible amount of inputs to produce a given level of output. These two definitions of technical efficiency lead to what are known as output-oriented and input-oriented efficiency measures respectively. Input-oriented efficiency scores range between 0 and 1.0, whereas output-oriented efficiency scores range between 1.0 to infinity; in both cases, 1.0 is efficient. The technical efficiency approach addresses the question of how efficiently services are provided to the clients, given the basket of inputs. This type of efficiency is known as 'Technical Efficiency'.

In this study, input-oriented measure was applied while the decision making units (DMUs) are the branches of POs. Input-oriented technical efficiency refers to the ability of DMUs to minimize input use in order to achieve given levels of output or assesses "how much can input quantities be proportionally reduced without changing the quantities produced?" (Coelli *et al.*,1998).

There are two principal arguments for the measurement of technical efficiency. Firstly, a gap exists between the theoretical assumptions of technically efficient firm practice and empirical reality i.e. a gap normally exists between a firm's actual and potential levels of technical performance (Leibenstein, 1966).

Secondly, there is a high probability that the existence of technical inefficiency will exert an influence on allocative efficiency and that there will be a cumulative negative effect on economic efficiency (Bauer, 1990; Kalirajan and Shand, 1988). For this reason, technical efficiency becomes central to the achievement of high levels of economic performance at the DMU level, as does its measurement.

A firm is said to be technically efficient if the firm is producing the maximum output from the minimum quantity of inputs, such as labor, capital and technology. The technical efficiency measure is the ratio of actual productivity (output per unit of input) and frontier (best practice) productivity (Wossink and Denaux, 2006).

Technical efficiency can be decomposed into two components: pure technical efficiency and scale efficiency. The pure technical efficiency is a measure of technical efficiency without scale efficiency and purely reflects the managerial ability to organize inputs in the production process. Thus, the pure technical efficiency measure has been used as an index to capture managerial performance.

The envelopment surface will differ depending on the scale assumptions. Generally, two scale assumptions are employed: constant returns to scale (CRS), and variable returns to scale (VRS). The pure technical efficiency measure is obtained by estimating the efficient frontier under the assumption of VRS. The measurement of technical efficiency (TE) under the assumption of CRS is known as total technical efficiency.

Scale efficiency is the measure of the ability to avoid waste by operating at, or near, to the most productive scale. Scale efficiency is measured by the ratio of total technical efficiency (TTE) and pure technical efficiency (PTE), which shows the institution's ability to choose the optimum scale of its operations. The scale efficiency can assume three forms, i.e., constant returns to scale, increasing returns to scale and decreasing returns to scale.

3. Review of Literature

3.1 Efficiency Studies of Microfinance Institutions in Bangladesh

Empirical studies on efficiency of MFIs around the world have shown different results, with the majority of them indicating that MFIs are not yet efficient in the use of their input resources.

Studies evaluating the efficiency of Bangladeshi MFIs in large scale are very rare to come across.

Rabbani *et al*. (2011) studied the productivity, efficiency and operational self-sufficiency of NGO-MFI branches of 16 POs that implemented PRIME. The operational self-sufficiency ratios depended on productivity of the branch and also on the efficiency. They showed that the branches established to implement PRIME typically exhibited lower loan size and higher cost in comparison with the branches that existed before PRIME was introduced. However, the ultra-poor programs evidently put some additional constraints on the performance of the MFI branches implementing PRIME. The PRIME branches did not show operational sustainability after three years of its operation.

Sinha (2011) analyzed performances of the ten largest microfinance institutions including Grameen Bank, BRAC and ASA. He showed that the number of active borrowers and portfolio size have increased steadily over time and their contribution to financial inclusion was substantial. Average loan balance has increased in real terms. MFIs have diversified financial services to include micro-insurance services. In Bangladesh, cost per borrower is one of the lowest worldwide, operational efficiency is high, and the yield has been stable in recent years, well below the interest cap of 27 percent charged on declining balance method.

Quayes and Khalily (2010) showed that the size of the MFIs matters and larger MFIs were more efficient than smaller MFIs. Amongst the big three, Grameen Bank and ASA were very close to the efficient frontier compared to BRAC. As smaller MFIs survive and grow, they undergo the process of learning efficiency. There was also some evidence of learning by all MFIs over time. However, proper utilization of resources deserves greater importance than the scale of operation.

3.2 Recent Studies of Efficiency on Microfinance Institutions in Other Countries

Ahmad (2011) evaluated how efficient microfinance institutions were in delivering credit to the poor in Pakistan. Data envelopment analysis was used to analyze the efficiency of these institutions. Both input oriented and output oriented methods were considered under the assumption of constant return to scale technologies and that microfinance should provide services on sustainable basis. They showed that only three MFIs out of twelve were efficient with decreasing efficiency trend. The average mean value of technical efficiency, pure technical efficiency, and scale efficiency were 57.1 percent, 70.9 percent, and 84.3 percent respectively under input oriented measure. This implies that input could be decreased by 29.1 percent without decreasing the output. The average technical efficiency, pure technical efficiency, and scale efficiency scores under output oriented measure were 57.1 percent, 73.4 percent and 78.8 percent respectively. In this case output could be increased by 26.6 percent with the existing level of inputs. No microfinance institution showed increasing return to scale under output oriented measure.

Hassan and Sanchez (2009) investigated technical efficiency and scale efficiency of MFIs in three regions: Latin America, Middle East and South Africa and South Asia countries. The authors found that technical efficiency was higher for formal MFIs (banks and credit unions) than non-formal MFIs (nonprofit organizations and non-financial institutions). Furthermore, the source of inefficiencies was found to be pure technical rather than the scale-related, suggesting that MFIs were either wasting resources or were not producing enough outputs (making enough loans, raising funds, and getting more borrowers).

Kipesha (2012) evaluated the efficiency of MFIs operating in East Africa using non- parametric DEA. The study used production approach to estimate efficiency scores of 35 MFIs under both constant and variable returns to scale. The results showed that MFIs in East Africa had high efficiency scores on average. The average technical efficiency scores were 0.71 (2009), 0.80 (2010) and 0.85(2011) under constant return to scale and 0.82, 0.89 and 0.89 under variable return to scale for three years respectively. The findings also showed that, on an average, the banks and non-bank financial institutions were more efficient compared to the NGOs and cooperatives

Martínez-González (2008) examined the relative technical efficiency of a sample of MFIs in Mexico, through the use of data envelopment analysis to compute efficiency scores, and through the estimation of a Tobit regression to identify determinants of the differences in efficiency. Results for the intermediation and production approaches suggest that most MFIs have been more efficient in pursuing sustainability (proxied by the performing loan portfolio size) rather than breadth of outreach (number of clients) or have not met either goal successfully, but this trend reverted in 2007. The significant determinants of differences in efficiency were: average size of loan, proportion of assets used as performing portfolio, scale of operations, ratio of payroll to expenses, age, structure of the board, and for-profit status of the MFI. The results portray an incipient market, where public funding does not necessarily lead to efficiency.

Nghiem and Laurenuson (2004) analyzed the efficiency and effectiveness of the microfinance institutions in Vietnam using both qualitative and quantitative approaches including DEA model. The average technical efficiency score was 80 percent. The authors concluded that most microfinance programs were fairly efficient.

The review of literature suggests that MFIs are technically inefficient across the globe, but the MFIs in Bangladesh have higher levels of technical efficiency score than those in Africa and other South Asian countries. In general, the studies showed that the inefficiency could be reduced by around twenty percent given the existing level of inputs. Loan size and age of MFIs are the critical determinants of technical efficiency. From above literature point of view, the crucial question is, to what extent PRIME branches are technically efficient? For this reason, the present study generate branch level efficiency score and find out the determinants of inefficiency.

4. Methodology

4.1 Data Source

This part of the study uses branch level data of all PRIME branches of POs. PRIME started its implementation from Lalmonirhat district in 2005 with only a limited number of branches. Over time, with the extension of PRIME to all other districts in the area, the number of branches increased to 237 at some point. Later on, some branches merged with other branches while some others died out. By the time the present survey was done during February-March 2013, the number of active branches was found to be 214. Financial and socioeconomic data for each of the 214 branches were collected by respective POs. Based on the intensity of PRIME members in MFIs branches operating under the PRIME program, we categorized the branches into two types. Some branches operated other micro finance program with PRIME; we call them 'PRIME branch'. Some branches do not have other programs at all; so we call them 'PRIME only branch'. Since we intend to carry out cross-sectional analysis for three different years, we restrict the sample size to 149 PRIME branches for which information were available for the years 2010 to 2012. However, PRIME only branches were selected using available information. The sample size was 40, 31 and 27 for PRIME only branches for the year of 2010 to 2012.

4.2 Data Analysis

The branch level data were the main source of information used for analysis. In this study, three categories of data analysis were needed to fulfill the research objectives. Descriptive statistic analysis was used to investigate the status of branches. DEA method was used to assess technical and scale efficiency. Finally, the descriptive and efficiency analysis results were used as variables in Tobit regression analysis to investigate the factors affecting the efficiency of PRIME branches.

4.3 Data Envelopment Analysis as an Approach to Efficiency Measurement

Coelli (1995), among many others, indicated that the DEA approach has two main advantages in estimating efficiency scores. First, it does not require the assumption of a functional form to specify the relationship between inputs and outputs. This implies that one can avoid unnecessary restrictions about functional form that can affect the analysis and distort efficiency measures, as mentioned in Fraser and Cordina (1999). Second, it does not require the distributional assumption of the inefficiency term.

The DEA is a non-parametric method because it does not require any assumptions for either the production function forms or the distribution of the efficiency error term. It constructs a non-parametric piecewise linear surface of production frontier over the data using linear programming (Banker *et al*., 1984, Charnes *et al.*, 1978, Fare *et al.*, 1983). The deterministic nature of the method makes DEA estimators sensitive to measurement errors of its component variables and outliers in the data.

The DEA model has been widely used in analyzing efficiency of financial institutions - such as studies by Portela and Thanassoulis (2007), Akhtar (2002), Sathye (2001), Aikaeli (2008), Farrier and Lovell (1990), Miller and Noulas (1996), Fixler and Zieschange (1993), Drake and Howcroft (1994), Athanassopoulos (1997), Hassan *et al*. (2004), Taylor *et al*. (1997) which used DEA to measure different aspects of efficiency in banking industry and studies such as Kipesha (2012), Bassem (2008), Qayyum and Ahmad (2006), Gutierrez-Nieto *et al*. (2009) and Nghiem *et al*. (2006) which used DEA to measure efficiency of MFIs.

DEA can estimate production frontiers for multiple inputs/ multiple outputs and assess where firm perform in relation to this frontier. Each firm thereby produces the same kind of output(s) using the same kind of inputs. DEA measures the level of efficiency by constructing an efficient frontier, which provides a yardstick for all decision making units (DMUs). The DMUs on the efficient frontier are the best practice performers within the sample, and are given a score of one, whereas other DMUs outside the efficient frontier are inefficient and given a score between zero and one (Charnes *et al.*, 1978)

The efficiency score in the presence of multiple input and output factors is defined as:

$$Efficiency = \frac{weighted\ sum\ of\ outputs}{weighted\ sum\ of\ inputs}$$

4.4 Model Specification of Technical and Scale Efficiency

The efficiency measurement methods used in this paper are derived from those presented in Fare *et al*. (1994), which are based upon the work of Farrell (1957), Afriat (1972), and Charnes et al. (1978)[2]. The estimation methods used in this research are explained below.

Assume that each branch produces multiple outputs y_i (e.g., loan outstanding and net savings) using a combination of inputs x_i (e.g. number of employees and fixed asset) and each firm is allowed to set its own set of weights for both inputs and output. The data for all firms are denoted by the K × N input matrix (X) and M × N output matrix (Y), where k denotes the number of employees, N denotes fixed asset, M stands for loan outstanding and N stands for net savings. Using piecewise technology, an input-oriented measure of technical efficiency can be calculated for the i^{th} firm as the solution to the following linear programming problem:

$$\begin{aligned} TE_i &= Min_{\theta,\lambda}\theta \\ \text{Subject to } & -y_i + Y\lambda \geq 0 \\ & \theta x_i - X\lambda \geq 0 \quad \text{.......................................}(1) \\ & \lambda \geq 0 \end{aligned}$$

2 For a comprehensive survey of DEA methodologies, see Lovell (1993), Ali and Seiford (1993), Färe *et al*. (1994), and Charnes, Cooper, Lewin and Seiford (1995).

In equation 1, θ is the TE score having a value $0 \le \theta \le 1$. If the value equals 1, the firm is on the frontier.

Coelli *et al*. (2005) pointed out that the CRS model is only appropriate when the firm is operating at an optimal scale. The VRS DEA frontier can be formulated by adding the convexity constraint: $N1\lambda = 1$, in equation (1) where N1 is an $N \times 1$ vector of ones and λ is an $N \times 1$ vector of constants.

The TE scores obtained from a CRS DEA can be decomposed into two components, one due to scale inefficiency and one due to pure technical inefficiency. This may be done by conducting both a CRS and a VRS DEA upon the same data. If there is a difference in the two TE scores for a particular firm, then this indicates that the firm has scale inefficiency, and that the scale inefficiency can be calculated from the difference between the VRS TE scores and the CRS TE score.

Given that the production technology is of the VRS type, scale efficiency 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):

$$SE_i = \frac{TE_{CRS}}{TE_{VRS}} \quad \text{...(2)}$$

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

5. Results and Discussion

5.1 Growth of Branches

The summary statistics as presented in Table 1 show considerable growth in terms of most indicators. The number of branches increased from 156 in 2008 to 214 in 2012. The number of active PRIME members, though decreased slightly from the year 2008 to the year 2009, consistently increased during 2009-2012. On an average, a branch had 1,011 active PRIME members in 2008, which was 68 percent of all active members. The proportion of PRIME active members to all active members steadily increased to 72 percent by 2012.

Table 1: Summary Statistics of PRIME branches: 2008-2012
Figures indicate branch average. (Monetary figures are in Taka)

Year	2008	2009	2010	2011	2012
Number of branches	156	206	210	210	214
Active member (PRIME)	1,011	1,025	1,180	1,216	1,248
Active member (All)	1,608	1,536	1,715	1,729	1,741
Borrowers (PRIME)	751	815	1,004	1,058	1,130
Borrowers (All)	1,377	1,339	1,520	1,577	1,621
Loan disbursement (PRIME)	3,311,184	4,569,731	6,184,201	8,487,774	9,602,194
Loan disbursement (All)	8,327,357	9,597,077	11,700,000	15,500,000	18,300,000
Total asset	6,528,839	7,099,554	8,355,433	10,700,000	12,600,000
Saving members	1,550	1,485	1,616	1,646	1,651
Av. loan outstanding (PRIME)	3,474	3,636	4,128	5,002	5,457
Av. loan outstanding (All)	4,425	6,187	4,694	5,784	7,247
Borrowers per staff (PRIME)	81	88	102	104	113
Borrowers per staff (All)	140	136	149	151	156
Loan outstanding/staff (PRIME)	257,713	297,620	365,029	467,838	472,181
Loanoutstanding/staff (All)	566,439	545,595	645,869	797,664	938,014
Total member per staff	166	156	168	167	158
PRIME member per staff	110	109	120	120	115
PRIME to total member ratio (%)	74	74	74	73.31	74.35
Borrower-member ratio total (%)	80	79	82.5	83.37	82.06
Borrower-member ratio prime (%)	70	75	78.3	78.39	77.59
PRIME loan outstanding (%)	70	76.3	68.3	87.05	59.95
Net savings per member	1,269	1,427	1578.881	2,090	2,568
Productivity indicators					
Input					
Number of Employees	10	10	10	11	11
Fixed asset	62,782	50,703	69,440	66,355	79,894
output					
Loan outstanding (PRIME)	2,356,087	2,694,429	3,623,435	4,773,148	5,225,250
Loan outstanding (All)	5,642,433	5,472,714	6,742,821	8,583,039	10,600,000
Net savings (TK.)	1,777,377	1,894,489	2,385,309	3,192,917	3,906,699

Source: PRIME branch level survey, 2013

Since MFIs provide small loans to clients, most members took advantage of accessing such loans. However, as Table 1 shows, during the period 2008-2012, borrower to total member ratio have increased over time. As we know that PRIME loan products are more flexible than other loan products, so it may be the most important reason behind this trend.

Loan disbursement under PRIME increased from around 3.3 million in 2008 to 9.6 million in 2012 - almost three-fold increase - while disbursement of loans under all programs doubled during the same period (Table1). The branch level average of total assets that include cash at hand, investment, loan outstanding and fixed assets increased to about 6.53 million in 2008 to

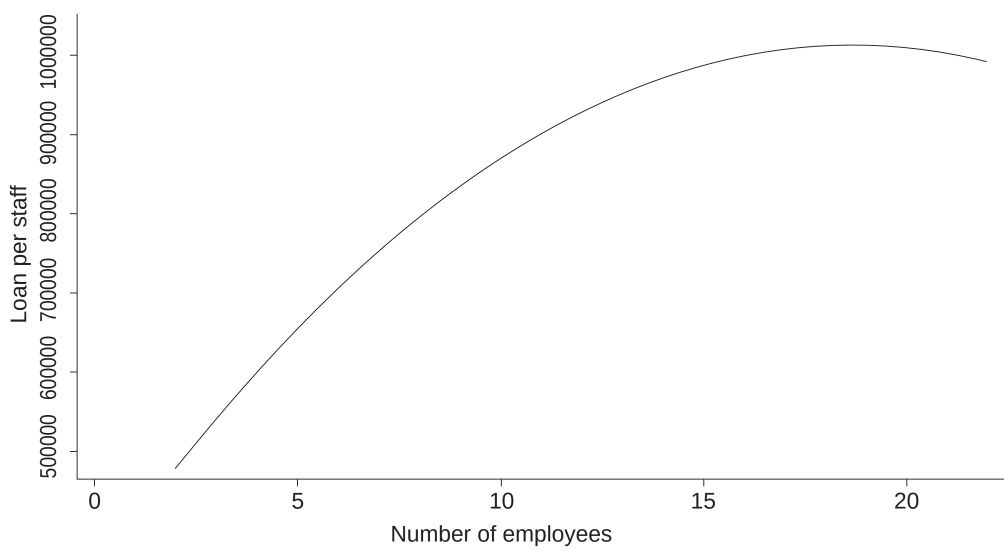
12.60 million in 2012. As most branches were small in size they used a tiny amount of fixed or physical assets - on an average, it was 0.06 million in 2008 and 0.08 million in 2012. The average number of staff in a branch was 10 during 2008 and it increased to only 11 during 2010-11. The number of staff along with loan operations indicates rise in staff productivity.

5.2 Productivity of PRIME Branches

All branches in the study areas use a similar technology of production (both input and output) except for differences in amount and management practices. Outputs were calculated in terms of taka values which are the dependent variable. Loan outstanding and savings were considered as outputs whereas the number of employees and fixed assets were considered as inputs. A number of earlier studies such as by Ahmad (2011), Annim, (2010), Masood and Alunad (2010), Haq (2010), Gutierrez-Nieto *et al*. (2009), Bassem (2008), Hermes *et al*. (2009, 2008), Hassan and Sanchez (2009), Kipesha (2012) used these variables for efficiency analysis of MFIs The selected productivity variables in different years are also shown in Table 1, which shows that PRIME loan outstanding increased from 2 million in 2008 to 5 million in 2012. During the period, all loan outstanding increased from 5.5 to around 11 million. Net savings increased from 1.7 million in 2008 to 3.9 million in 2012. The PRIME loan outstanding increased more compared with all loans outstanding, which means branches have become more capable to finance themselves.

As most MFIs used a small amount of fixed assets and labor cost constitutes the main component of the total cost of production, it is necessary to know the status of labor productivity at the branch level. This is shown in Figure 1. The average loan per staff increased in tandem.

Figure 1: Average productivity of labor



But beyond a certain level, any increase in employment may reduce productivity. In an average PRIME branch, the optimum loan outstanding per staff is approximately one million taka and the critical value of staff for handling that amount is 18.

Staff loan productivity shows an increasing trend at a decreasing rate. But it continued to increase for the branches with 10 employees. Beyond this point, the branches showed a decreasing rate of growth in average loan productivity. This could be due to several factors: (i) branches with 10 or less staff operate more in less risky areas, and (ii) human resources for the branches with 15 or more are under-utilized. This needs to be clearly examined from the perspective of optimum staff size of a branch.

5.3 Efficiency Estimates of PRIME Branches

The non-parametric DEA models which are described in section 4 were estimated by using computer software, STATA version 12. The empirical estimates of efficiency and its components of PRIME branches as well as PRIME only branches in *monga* areas are shown in Figure 2 to Figure 5.

The average technical efficiency score indicates that PRIME branches operating in *monga* areas could reduce their input resources by around 20 percent under CRS and by around 11 percent for three years under VRS for them to be efficient without affecting the output levels (Figure 2). However, the average scale of efficiency scores was found to be 0.90 for the 2010 to 2012 respectively, indicating an average of 10 percent divergence from most productive scale among branches.

PRIME only branches operating in *monga* areas could reduce their input resources by around 20 percent for three years under CRS and by around 15 percent for three different years under VRS for them to be efficient without affecting the output levels (Figure 3).The average scale of efficiency score was about 0.94 for the year of 2010 to 2012, indicating an average of 6 percent variation from most productive scale among PRIME only branches as shown in Figure 3.

The average scale efficiency results were higher than the average pure technical efficiency results in all three years; this implies that the source of technical inefficiency is generally due to pure technical inefficiency resulting from misallocation of inputs in the production of outputs. Similar result was found by Singh *et al*. (2013) in their study of microfinance in India. Kipesha (2012) also noted similar findings in case of efficiency analysis of MFIs in East Africa. Quayes and Khalily (2010) found that PKSF's partners were more efficient than those who were not PKSF POs. The efficiency of PKSF partners can be attributed to their uniform disclosure and organizational practice.

Figure 2: Average total technical (TE_{CRS}), pure technical (TE_{VRS}), and scale efficiency (SE) scores of PRIME branches

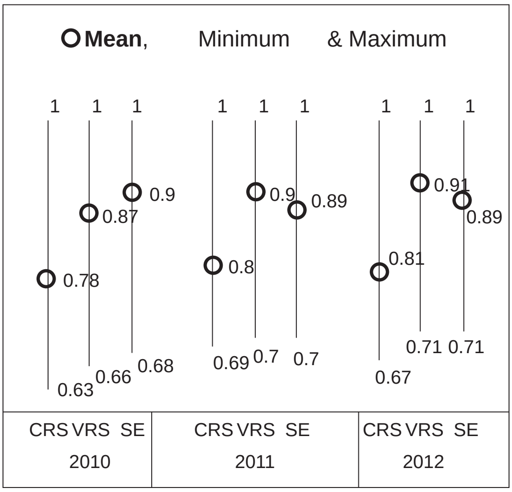
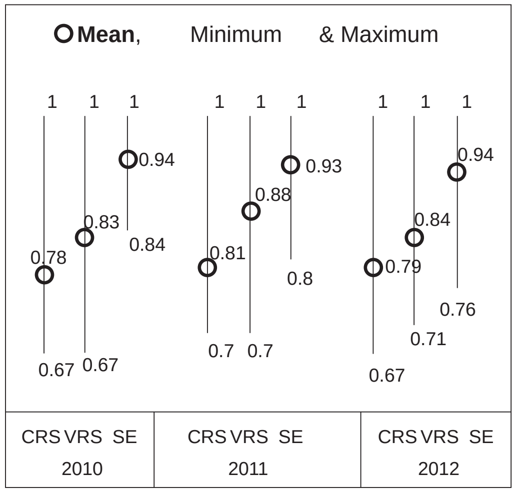


Figure 3: Average total technical (TE_{CRS}), pure technical (TE_{VRS}), and scale efficiency (SE) scores of PRIME only branches



The average scale efficiency score was more or less similar over the branches. So, we can easily construct a graph and compare the results of return to scale in the last two years. The return to scale results indicated that 4 branches were fully efficient in 2011 and 2012 at constant return to scale. The results also indicated that around 11 percent of branches were at the stage of increasing return to scale for the last two years while 87 percent of PRIME branches were at decreasing return to scale (Figure 4). This implies that most of the branches in the area do not operate at optimal scale with only few branches operating at constant return to scale. However, over time, the results showed a constant trend and most of the branches were operating at decreasing return to scale (Figure 4 and Figure 5). Figure 5 show that there was a trend of increasing and constant return to scale over the years. However, the most surprising result was that only one or two branches were fully efficient in 2011 and 2012 at constant return to scale.

Figure 4: Returns to scale among PRIME branches

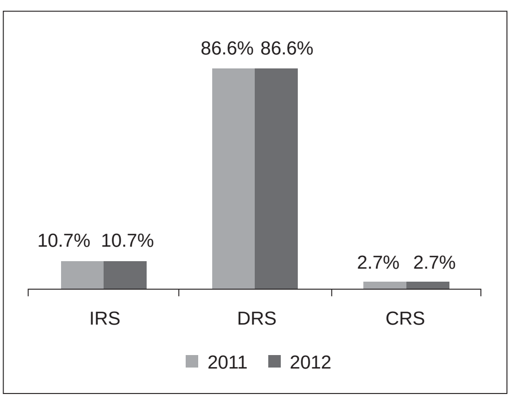
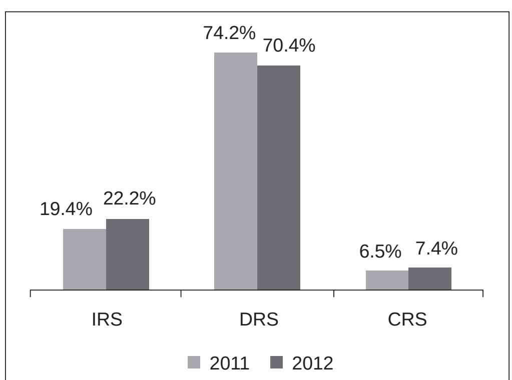


Figure 5: Returns to scale among PRIME only branches



Frequency distribution of total technical, pure technical, and scale efficiency estimates of PRIME branches are given in Figure 6 to Figure 8. It is evident from Figure 6 that more than 60 percent of the branches operated below 80 percent of total technical efficiency level over time. Moreover, around 80 percent of the PRIME branches had a tendency to operate greater than 80 percent pure technical efficiency level. Majority of the branches achieved pure technical and scale efficiency greater than 0.80 over time (Figure 7 and Figure 8).

Figure 6:Frequency distribution of total technical efficiency of PRIME branches over time

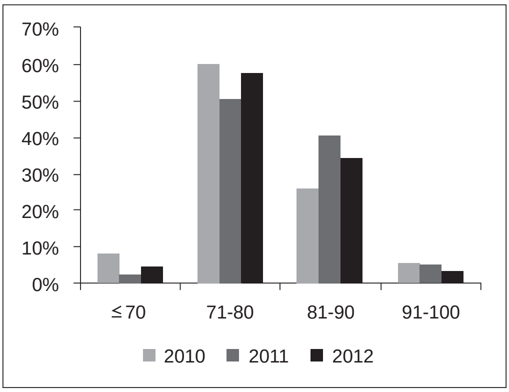


Figure 7:Frequency distribution of pure technical efficiency of PRIME branches over time

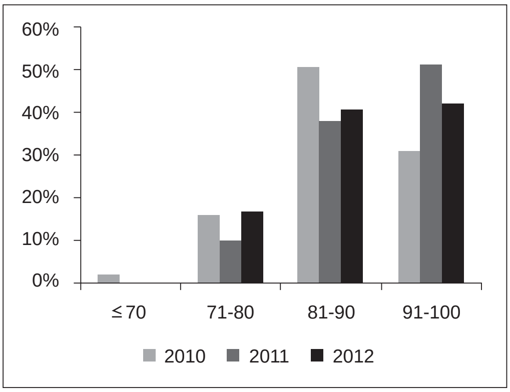
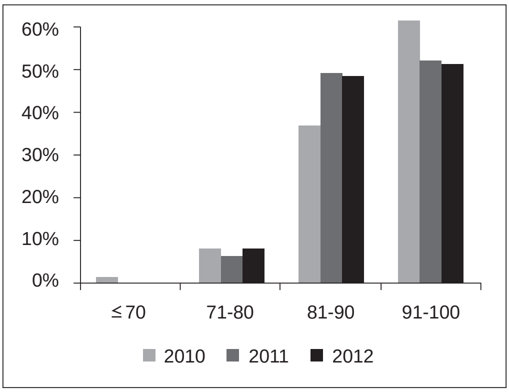


Figure 8:Frequency distribution of scale efficiency of PRIME branches over time



In brief, we find that technical efficiency score of PRIME branches has increased over the period 2010-2012 but the level of efficiency of PRIME only branches decreased slightly from 2011 to 2012. All the results imply that the branches had higher ability to use input resources efficiently to max output. But the question is who are more efficient? What is the main reason for this variation of efficiency score? In order to assess this we used Tobit.

5.4 Determinants of Efficiency

5.4.1 Tobit Regression Analysis

A question of great interest for policy makers is: why efficiency differentials occur across the firms of the same firming system? They may be the reflection of managerial ability and skill of a firm's operator and interaction of various socioeconomic factors. We propose different variables that can explain the efficiency of MFIs. These variables can be divided into different groups based on location, basic characteristics, financial management and performance.

Identifications of such factors will help the existing MFI to increase their efficiency level (Elyasiani and Mehdian 1990; Isik and Hassan 2003; Masood and Ahmad, 2010; Sing *et al.*, 2013). The present study made an attempt to investigate the impact of these variables on technical efficiency of MFIs in Bangladesh. Since the dependent variable, efficiency, is a censored variable with an upper limit of one (Lockheed *et al.*, 1981), it is pertinent to use the Tobit model, which is a censored regression model, applicable in cases where the dependent variable is constrained in some way. Thus, in the present format of Tobit model analysis, it is customary to regress the DEA efficiency scores on the relevant control variables (Luoma *et al.*, 1998; Fethi *et al.*, 2000; Chilingerian, 1995; Hwang and Oh, 2008).

5.4.2 Tobit Model Specification

The Tobit model may be defined as:

$$Y = \begin{cases} y^*; & 0 <= y^* <= 1 \\ 0; & y^* < 0; \\ 1; & 1 < y^* \end{cases}$$

$$y^* = \beta x_i + \varepsilon_t \qquad \text{..........(3)}$$

Where

Y= is an efficiency measure representing total technical and pure technical efficiency of the i^{th} firm. $\varepsilon_t \sim N(0, \sigma^2)$;

y* is a latent (unobservable) variable;

β is the vector of unknown parameters which determines the relationship between the independent variables and the latent variable;
x_i is the vector of explanatory variables.

Thus, the Tobit model used in this study may be specified as

$$y^* = \alpha + \beta_1 BA + \beta_2 ED + \beta_3 PT + \beta_4 BS + \beta_5 GI + \beta_6 KU + \beta_7 LM + \beta_8 NL + \varepsilon_t \qquad \text{..........(4)}$$

Where

y* is the dependent variable (Total technical, pure technical and scale efficiency of PRIME branches), and ε is the error term.

The literatures from previous studies indicate that a range of socioeconomic factors are likely to affect the capability of a producer to efficiently utilize the available technology. In the context of microfinance institutions, similar variables were considered as relevant which are shown in Table 2.

Table 2: Variables definition for factors associated with efficiency

Variables	Symbol	Definition
Branch age	BA	Branch age is a measure of the experience of the branch, i.e., the number of years of operations since its establishment.
Education	ED	Level of education completed by branch manager
PRIME to total member ratio	PT	PRIME to total member ratio. It is the ratio of active member of PRIME to total active member in the branch
Borrower per staff	BS	Borrower per staff. It is derived from number of borrowers at the end of the year of the branch divide by number of employee
Gibandha	GI	Dummy variable to measure the influence of branch location established in Gibandha areas on efficiency. Value is 1 if the branch established in Gibandha, and o Rangpur.
Kurigram	KU	Dummy variable to measure the influence of branch location established in Kurigram districts on efficiency. Value is 1 if the branch established in Kurigram, and 0 for Rangpur.
Lalmonirhat	LM	Dummy variable to measure the influence of branch location established in Lalmonirhat districts on efficiency. Value is 1 if the branch established in Lalmonirhat, and 0 for Rangpur.
Nilphamari	NL	Dummy variable to measure the influence of branch location established in Nilphamari districts on efficiency. Value is 1 if the branch established in Nilphamari, and 0 for Rangpur.

5.4.3 Descriptive Statistics of Variables Used in Tobit Analysis

It is necessary to identify the major socioeconomic factors which are responsible for variation in efficiency scores over the PRIME branches.

Table 3 shows the summary statistics of all branches which were categorized as branch characteristics and village-specific characteristics of the PRIME branches.

Table 3: Summary statistics of variables used in Tobit analysis for the year of 2012

Variables	Mean
Number of observations	149
Branch characteristics	
PRIME to total member ratio	0.78
Borrower per staff	164
Female to total staff ratio	0.30
Branch age (years)	7
Age of operating PRIME (years)	5.5
Managerial characteristics	
Age of branch manager (years)	35
Education (years)	16
Experience in Current Branch as manager (months)	19

Variables	Mean
Number of training attended	4
Number of financial training attended	2
Village-specific branch characteristics	
Distance from sub-district/Upazila centre (km)	8.70
Number of MFIs within 5 km radius	8
Percentage of literate people in union	64
Percentage of credit holders living in char area	13

Source: PRIME branch level survey, 2013

We are interested to know more about the PRIME branches based on their efficiency levels in the current year (2012). We have categorized the branches into four types on the basis of efficiency score distribution (Table 4). A branch is categorized as (1) 'highly efficient' if the efficiency score is 0.87 or more, (2) 'moderately efficient' if the score is above 0.80 or below 0.87, (3) 'weakly efficient' if it is above 0.76 and below 0.80, and (4) 'inefficient' if the score is above 0.71 and below 0.76.

Table 4 shows that branches are highly efficient if they have higher number of borrower per staff. However, the higher the productivity of the worker, the more efficient is the institution. The variation of productivity levels of staff across the branches can be explained by the capacity of the MFI to attract skilled personnel, the degree of motivation, salary structure and other incentives to output; and also may be as a result of the marketing strategy of the microfinance institution. Table 5 also confirms that borrower per staff is positively and highly significant to technical efficiency. This finding proves that the performance of the staff has a significant impact on efficiency of the MFIs which was similar to the findings of Oteng-Abayie et al. (2011). Nevertheless, managerial characteristics do not have much influence on determining efficiency level, except for the experience of branch manager. The branches are highly pure technical efficient if the branch manager has higher experience. This can be attributed to learning by doing. But the result was different for scale efficiency due to the scale of operation (Table 4). Consequently, the village-specific or location characteristic of the branch has an impact on efficiency although these variables had no significant relationship with efficiency. The branches are more efficient if the distance from Upazila increases because in distant areas very few MFIs are found. If the number of other MFIs within 5 km are very few, then the branch is more efficient due to the monopolistic nature. However, the location with more educated people shows a higher tendency of efficiency of the branches (Table 4).

Socioeconomic and firm specific factors are likely to affect the level of total technical, pure technical and scale inefficiency of branches. The present study makes an attempt to investigate the factors associated with efficiency. In order to identify sources of technical, and scale efficiency, the inefficiency estimates were separately regressed on socioeconomic and firm specific variables, respectively by using Tobit regression model. The coefficients of explanatory variables in Tobit regression models are of particular interest in terms of understanding the efficiency differentials among the branches and for making policy options. The estimated coefficients are very small because the dependent variable (efficiency score) varies from zero to one by definition. Determinants of efficiency of PRIME branches are presented in Table 5.

Table 4: Broader determinants of efficiency (2012)

Variables	Total technical efficiency				Pure technical efficiency				Scale efficiency			
	Highly efficient	Moderately efficient	Weakly efficient	Inefficient	Highly efficient	Moderately efficient	Weakly efficient	Inefficient	Highly efficient	Moderately efficient	Weakly efficient	Inefficient
Average efficiency score	0.87	0.8	0.76	0.71	0.98	0.91	0.85	0.78	0.98	0.93	0.87	0.81
Branch characteristics												
PRIME to total member ratio	0.7	0.86	0.81	0.74	0.64	0.72	0.95	0.79	0.99	0.76	0.69	0.66
Borrower per staff	239	148	144	126	231	156	155	114	221	137	153	148
Female to total staff ratio	0.3	0.29	0.38	0.25	0.25	0.31	0.37	0.28	0.32	0.38	0.27	0.24
Branch age (years)	7	8	6	8	9	7	6	7	7	6	7	9
Age of operating PRIME (years)	6	6	6	5	6	5	6	5	6	5	6	6
Managerial characteristics												
Age of branch manager (years)	36	35	34	35	35	35	34	34	34	34	36	35
Education (years)	15	15	16	16	15	16	16	15	15	16	16	16
Experience in Current Branch as manager (months)	17	19	19	21	23	20	16	18	16	18	20	22
Number of training attended	3	3	3	4	4	3	3	3	3	3	3	4
Number of financial training attended	2	2	2	2	2	2	2	2	1	2	2	2
Location characteristics												
Distance from sub-district/ Upazila centre (km)	12.3	9.1	8.5	5	8.5	11.4	7.8	7.2	11.3	7.41	9.64	6.59
Number of MFIs within 5 km radius	6	7	7	11	7	6	9	10	7	9	8	7
Percentage of literate people in union	68	61	66	63	69	60	63	67	67	66	63	63
Percentage of credit holders living in char area	7	16	10	17	10	17	10	15	10	13	18	10
Number of observations	38	37	37	37	37	37	38	37	38	37	36	38

Table 5: Determinants of efficiency of PRIME branches

Variables	**TE_{CRS}**	**TE_{VRS}**	**SCALE**
Branch age	-0.00236*	0.00427**	-0.00524***
	(0.00140)	(0.00213)	(0.00145)
Education	-0.00282	0.000134	-0.00371
	(0.00339)	(0.00501)	(0.00352)
PRIME to total member	-0.00150	-0.0251*	0.0231**
	(0.00943)	(0.0138)	(0.00976)
Borrower per staff	0.000102**	0.000216**	.0000331
	(.0000423)	(0.000103)	.0000248
Gaibandha	0.0455***	0.00623	0.0388***
	(0.0134)	(0.0199)	(0.0139)
Kurigram	0.00981	0.0394*	-0.0324**
	(0.0151)	(0.0224)	(0.0156)
Lalmonirhat	0.0202	0.0259	-0.00553
	(0.0185)	(0.0273)	(0.0191)
Nilphamari	0.0397**	0.0552**	-0.00830
	(0.0157)	(0.0232)	(0.0162)
Constant	0.807***	0.820***	0.964***
	(0.0567)	(0.0845)	(0.0584)
Observations	149	149	149
Log likelihood	199	114	196

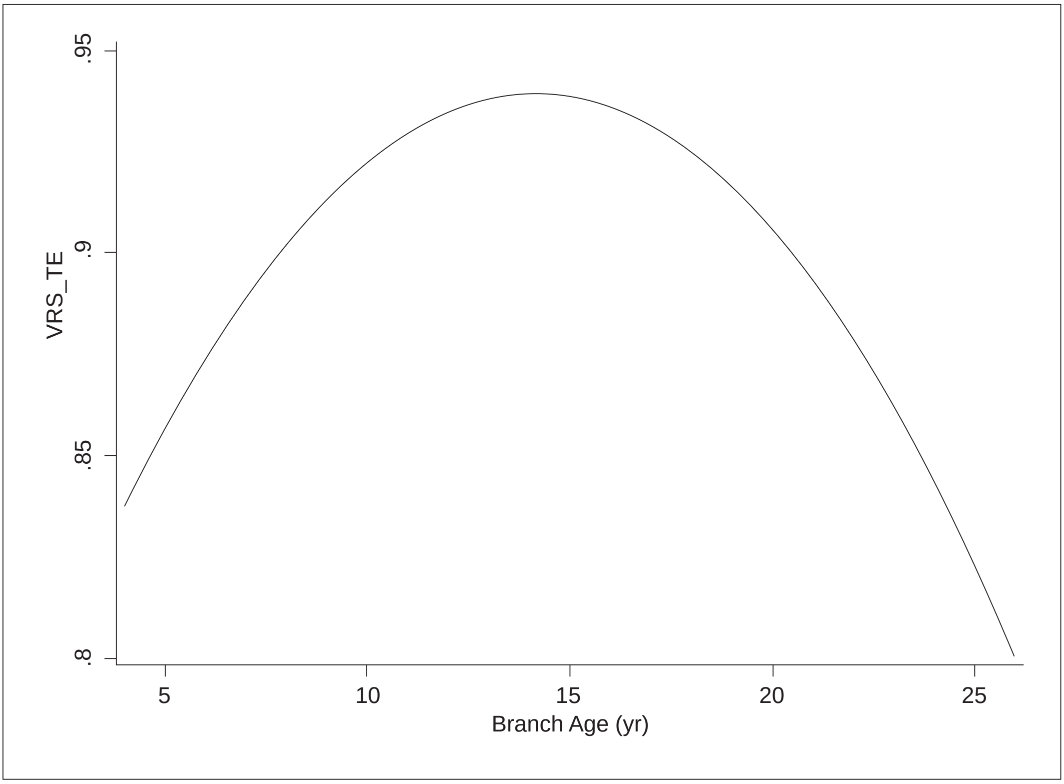
Standard errors are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

From Table 5, the coefficient of the branch age variable was significant to technical and scale efficiency. The branch age showed a negative relationship with total technical and scale efficiency because the firm cannot operate on a large scale if the firm is older in age. The positive coefficient of branch age suggests that inefficiency reduces as the branch age increases. The older branches were more technically efficient than the younger ones. However, from this finding it is clear that as the age of branches increases, the efficiency level will also increase. This goes to confirm the importance of experience in the branches, as the evidence shows the existence of a learning curve affects the sector. This is consistent with the findings of Tariq *et al.* (2008), Oteng-Abayie *et al.* (2011) in their microfinance study.

Figure 9 also shows that as the branch age increased, the pure technical efficiency increased exponentially over time with an increasing rate initially up to thirteen years but after a certain period of time efficiency does not increase because the older firms cannot operate on large scale.

The PRIME to total member ratio was negatively and significantly related to pure technical efficiency. This is due to the fact that, accepting an ultra-poor program like PRIME program might affect the productivity and efficiency of a branch initially (for MFI level discussion, see Cull *et al.*, 2007). However, a positive and significant relationship to scale efficiency showed that increasing the intensity of such service (by increasing PRIME to total member ratio) productivity and efficiency rises, due to augmented homogeneity of service and more symmetric information with the product over time.

Figure 9: Pure technical efficiency of PRIME branches over the years of operating branch



The location variable Kurigram was more technically efficient under variable return to scale and less scale efficient compared to Rangpur district. However, it was also found that Nilphamari district was more technically efficient compared to Rangpur district (Table 5). This promising result suggest that for expanding PRIME branches in future, selection of proper location will help to achieve higher efficiency.

6. Conclusions and Suggestions

DEA was applied to estimate the efficiency of PRIME branches in three different years by means of input-oriented approach in the selected five districts in *monga* region of Bangladesh. In all, efficiency analysis results showed that there was a considerable amount of inefficiency and a substantial potential for increasing loan and savings through the improvement of total technical, pure technical, and scale efficiency. The findings showed that over time, the efficiency increased although the rate was slow. In 2012, the findings suggested that the same level of outputs of PRIME branches could be obtained by reducing the inputs (i.e. Number of personnel and fixed asset) by 10 to 21 percent. The pure technical efficiency is greater than the total technical efficiency. Furthermore, the surprising result was that only 3 percent (4 out of 149) of branches were found realizing constant returns to scale whereas 87 percent of firms were found decreasing returns to scale. Hence, there was substantial capacity to augment the outputs or to reduce inputs in total branches.

Additionally, a second stage Tobit regression shows that the variation is also related to firm-specific attributes such as branch age, PRIME to total member ratio, borrower per staff, and location. From the above findings, it is recommended that branches should improve their efficiency through better use of resources and reducing the amount of wastes. Since PRIME is an ultra-poor program, it is, therefore, suggested that achieving higher efficiency might take a long time since old branches were more efficient than new ones. It is also suggested that by occupying more skilled labor, borrower per staff will be increased in the study areas. However, Kurigram was less scale efficient and Nilphamari was more technically efficient in contrast to Rangpur district. This potential result also proposes that for expanding PRIME branches in the future, selection of appropriate location will help to achieve higher efficiency. The policy implication of the study establishes that inefficient branches can also achieve higher level of efficiency with strong fundamentals, selection of appropriate location, rational policy and management.

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