Wadud, International Journal of Applied Economics, 17(1), March 2020, 39-47

Does Matching help Assessing the Impact of Microcredit on Farm Efficiency: Evidence from Bangladesh

Md Abdul Wadud
Rajshahi University, Rajshahi 6205, Bangladesh

Abstract: Matching is gaining popularity in evaluating program impact. Applying the stochastic frontier approach, this paper aims to assess the impact of microcredit on the efficiency of farms which are selected through propensity score matching which pairs treatment and control units with nearest values on the propensity score. We use farm level data of a sample of 682 farms of which 450 are microcredit receivers and the rest 232 are microcredit non-receivers. After matching, we select 165 farms from both categories. Results report a positive impact of microcredit on efficiency of farms; this implies that the efficiency of microcredit receiving farms is 1.63 per cent higher than those of microcredit non-receiving farms. This could contribute to the higher production, farm income and sustainable livelihood of rural farming families. Thus this study can provide significant implications to policymakers and implementers in agriculture of developing countries like Bangladesh.

Keywords: Propensity Matching Score; Microcredit; Farm Efficiency; Bangladesh

JEL Classification: Q1, C13.

1. Introduction

Propensity score matching (PSM) refers to the pairing of treatment and control units with similar values on the propensity score. 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) discuss the usage of matching in pharmacoepidemiologic research. Hitt and Frei (2002) analyse the effect of online banking on the profitability of customers. Davies and Kim (2003) compare the effect on the percentage bid-ask spread of Canadian firms being interlisted on a US Exchange, whereas Brand and Halaby (2006) analyse the effect of elite college attendance on career outcomes. Ham *et. al.* (2004) study the effect of a migration decision on the wage growth of young men. Bryson et.al. (2002) analyse the effect of union membership on wages of employees.

Microcredit [1] is a widely discussed issue and there is a great debate whether it can have a positive impact on farm efficiency and income. Microcredit is assumed likely to contribute both directly and indirectly to agricultural farming efficiency and income. Agriculture in Bangladesh is characterized by a large number of small and marginal farms with limited financial resources and hence farmers can not apply optimal inputs and new production technologies for higher production. This results in lower production and farm income, and timely and proper application of inputs like fertilizer, pesticides and irrigation is important for higher production. Therefore, cash for the purchase of seeds, chemical fertilizers, pesticides and mechanical equipment is of utmost importance.

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 microcredit. As marginal and small farmers have little or no access to formal sources of microcredit, microcredit can provide them access to inputs like seed, fertilizer and irrigation at proper time. This, in turn, helps use of new production technologies, thereby increasing farm efficiency, food production, farm income and sustainable livelihood.

Like many other developing countries, the government of Bangladesh, Palli Karma-Sahayak Foundation (PKSF) and other institutions have started funding in agricultural activities. Use of microcredit in agriculture has been on the increase and now it constitutes about 40 percent of all credits that the farmers receive. *A priori,* it is thought that microcredit could have a positive impact in enhancing efficiency performance of farms, farm income of marginal and small farmers and hence improving their status of livelohood.

Since the seminal pioneering work of Farrell (1957), numerous researches (Coelli, et. al., 2002; Wadud and White, 2000; Battese, 1992; Battese and Coelli, 1992; Iraizoz, et. al., 2005; Kotzian, 2009; Khoshroo et.al, 2013; Caiazza, et.al., 2016; Akamina, et.al., 2017; Khan et.al., 2017; Parichatnon, 2018; Agyemang, Ratinger and Ahado, 2019; Edet, Agbachom and Uwah, 2019; Hossain, et. al., 2019 and Lawin, Tamini and Bocoum, 2018) assess efficiency in various sectors applying different specifications of measurement, no research takes an attempt to evaluate the impact of microcredit on farm efficiency between matched treatment and control group. This research, therefore, is designed to achieve this objective using farm level survey data of developing like Bangladesh. To the best of my knowledge, this research is first of its kind.

The rest of the paper is organized as follows. Section 2 describes the empirical framework and data; Section 3 gives results and Section 4 provides conclusion of the study.

2. Empirical Framework and Data

The methodology of this research comprises propensity score matching technique and the general stochastic frontier production model. While the former matches the program participants (treated) with non-participants (controlled), the latter estimates the efficiency of the treated and controlled farms. These are described as follows.

2.1 Propensity Score Matching

Matching is a widely-used non-experimental method of evaluation that can be used to estimate the average effect of a particular program.[2] This method compares the outcomes of program participants with those of matched non-participants, where matches are chosen on the basis of similarity in observed characteristics or covariates. Since conditioning on all relevant covariates is limited in the case of a high dimensional vector X ('curse of dimensionality'), Rosenbaum and Rubin (1983b) suggest 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 program given observed characteristics X. Matching procedures based on this balancing score are known as propensity score matching (PSM). Suppose there are two groups of farms indexed by participation status $P = 0/1$, where 1 (0) indicates farms that did (not) participate in a program. 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, $ATT = E(Y_1 - Y_0 | p = 1) = E[(Y_1 | p = 1)] - E[Y_0 | p = 1]$, which answers the following question: 'How much did farms participating in the program benefit compared to what they would have experienced without participating in the program?' Data on $E[(Y_1 | p = 1)]$ are available from the program participants. An evaluator's 'classic problem' is to find $E[Y_0 | p = 1]$, since data on non-participants enables one to identify $E[Y_0 | p = 0]$ only. So the difference between $E[(Y_1 \mid p = 1)]$ and $E[Y_0 | p = 1]$ cannot be observed for the same farm.

The solution advanced by Rubin (1979) is based on the assumption that given a set of observable covariates $\boldsymbol{X}$, 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, $[E(Y_0 | P = 1, X) = E(Y_0 | P = 0, X)]$. This permits the use of matched non-participating farms to measure how the group of participating farms would have performed, had they not participated.

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 nonparticipants as an approximation is not advisable, since participants and nonparticipants 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 program and also have a higher probability of finding a job. The matching approach is one possible solution to the selection problem. Evaluation studies attempt to estimate the mean effect of participating in a program (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, 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).

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.

Using PSM techniques, we identify the matched treated (microcredit receiving farms) and control farms (microcredit non-receiving farms) to further evaluate the impact of microcredit on farm efficiency.

2.2 Stochastic Frontier Approach to Efficiency Estimation

We apply the stochastic frontier model (Aigner et al., 1977; and Meeusen and van den Broeck, 1977) to estimate technical efficiency. The general stochastic frontier production model is defined as:

$$y_i = f(x_i;\beta)e^{u_i} \tag{1}$$
$$u_i = \xi_i - \zeta_i,\ \ i = 1,2,3,\ldots,q,\ \ -\infty \le \xi_i \le \infty \ \text{ and } \ \zeta_i \ge 0.$$

where y_i represents the output of the ith farms, x_i indicates 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, takes account of measurement error and captures exogenous shocks and factors not under the control of the farms; The asymmetric non-negative random errors, ζ_i, which are called technical inefficiency effects, account for technical inefficiency in production.

Assuming a probability density function for both ξ_i and ζ_i, we can estimate (1) by maximum likelihood methods. The variance parameters are expressed as:

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

The total variation γ of output from the production frontier which can be attributed to technical efficiency (Battese and Corra, 1977). If $\gamma \to 0$ then $\sigma_\zeta^2 \to 0$ and $\sigma_\xi^2 \to \sigma_u^2$, 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 output and frontier output can be attributed to differences in technical efficiency.

Thus the technical efficiency of each industry is estimated as:

$$\therefore \qquad \varphi_i = \left[\frac{1-\Phi\left\{\sigma_i^* - \left(\mu_i^*/\sigma_i^*\right)\right\}}{1-\Phi\left(-\mu_i^*/\sigma_i^*\right)}\right] e^{\left(-\mu_i^* + \frac{1}{2}\sigma_i^{*2}\right)} \tag{3}$$

The mean technical efficiency of all industries in the sample, $\bar{\varphi}$, is obtained as:

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

We conducted a survey on 682 farms of which 450 are microcredit receivers and the rest 232 are microcredit non-receivers using a structured questionnaire in 2009. The questionnaire included questions about household characteristics such as microcredit, experience, education, land fragmentation and land size of farm households.

Wadud, International Journal of Applied Economics, 17(1), March 2020, 39-47

3. Empirical Results: Propensity Scores, Efficiency and Program Effect

Calculation of the propensity score of the first step of find a program effect. We apply the specification of logistic regression model[3] 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. Results are given in Table 1.

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

We obtain matched treated and control farms of 165 and 165 respectively. We now apply the Cobb-Douglas stochastic frontier approach[4] to estimate efficiency of each of the farms. Results are given in Table 1 and 2. While Table 1 shows results of number of farms of microcredit receivers and microcredit non-receivers according to efficiency index or cohorts, table 2 arranges summary statistics of results exhibiting mean, standard deviation, maximum, minimum and their coefficient variations, and microcredit program effect. We find from Table 1 that numbers of microcredit receiving farms in the efficiency 0-50, 50-60, 60-70 and 80-90 cohorts are more than those of microcredit non-receiving farms in the same cohorts. More microcredit receiving farms are concentrated in the efficiency cohort 80-90. This implies that microcredit pushes the farms from lower efficiency groups to higher efficiency groups. In the efficiency cohort 90-100, the numbers of microcredit receiving farms are less than those of non-receiving farms. This is because there are well-off and financially farms which do not require microcredit to operate their farm activities.

At the lower part of Table 2 provides the microcredit impact on the efficiency of farms that microcredit receiving farms are 1.63 percent more efficient that their microcredit non-receiving counterparts with a value of coefficient of variation of 1.39 percent. Table 2 also shows that variation of efficiency across microcredit receiving farms is lower than that of microcredit non-receiving farms, although maximum efficiency of microcredit non-receiving farms is little high. This result is consistent with the result of accumulation of more microcredit non-receiving farm in the higher efficient cohort.

Results from both Tables imply that the microcredit program as a whole has had a favourable and positive impact on the efficiency of farms and that the microcredit receiving farms operate their farming activities with 1.63 percent lower cost than their microcredit non-receiving farms. The implication of these results are that supplying of microcredit to marginal and small farms could reduce farming cost, improve efficiency, farm income and hence ensure sustainable livelihood of farm families.

4. Conclusions

This study aims to assess the impact of microcredit on the efficiency of farms using survey data a sample of 682 farms of which 450 are microcredit receivers and the rest 232 are microcredit non-receivers. After matching, 165 farms of each group of microcredit receivers (treatment group) and microcredit non-receivers (control group) are obtained and the Cobb-Douglas stochastic frontier model is applied to calculate the efficiency of farms, and hence obtain the impact of microcredit on efficiency. Results reveal that matching plays a significant role of finding matched treated and controlled pairs from where impact of microcredit is achieved through estimation of efficiency. Results show that the efficiency level of the treated group (microcredit receivers) is, on an average, 1.63 percent higher than that its control group (microcredit non-receivers). Results also exhibit that microcredit pushes farms from lower efficiency groups to higher efficiency groups. Therefore, policies leading to the extension, and fair, timely and low-cost delivery of microcredit to marginal and small farmers could lead to the increase in farm efficiency, output and income that could help ensure food security of agrarian poor people of a developing country like Bangladesh. Moreover, this approach can be used in other sectors for impact assessment.

Endnotes

[*]Professor, Department of Economics, Rajshahi University, Rajshahi 6205, Bangladesh; Email: wadud68@yahoo.com.

1. Microcredit is defined as very small loan to poor borrowers who typically lack collateral and sustainable employment, and are excluded from the traditional banking system. 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.

2. 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).

3. The logit model in which the dependent variable is a dummy implying whether the farm is participating the programme (receiving credit) or not-participating (not-receiving credit) is given as:

$$Pr(D_i = 1|X_i) = \frac{1}{1 + e^{\left(-x_j'\beta\right)}}$$

The probability of one matched farm receiving treatment is defined as:

$$p(X_i) = Pr(D_i = 1|X_i) = E(D_i|X_i)$$

The distribution of characteristic or covariates among treated and controlled farms should be similar. The propensity score is used to evaluate whether the differences between groups, after matching, is not statistically different.

4. The Cobb-Douglas production stochastic frontier has been widely used in econometric analysis. This frontier is specified as:

$$\ln y_i = \beta_0 + \sum_{i=1}^{q} \beta_i \ln x_i + u_i$$

where y_i = 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 to each input and the production function is homogeneous of degree $\sum_{i=1}^{n} \beta_i$ which is also the returns to scale.

References

Agyemang, S. A., T. Ratinger, and S. Ahado. 2019, "Has microcredit boosted poultry production in Ghana?" Agricultural Finance Review, 76(2):309-324.

Akamina, A., J. Bidogeza, J.R. Minkoua and V. Afari-Sefa. 2017, "Efficiency and productivity analysis of vegetable farming within root and tuber-based systems in the humid tropics of Cameroon," Journal of Integrative Agriculture, 16, 1865– 1873.

Battese, G.E. and T.J. Coelli. 1992, "Frontier production functions, technical efficiency and panel data: with application to paddy farmers in India," Journal of Productivity Analysis, 3,153–169.

Battese, G.E. 1992, "Frontier production functions and technical efficiency: a survey of empirical application in agricultural economics," Agricultural Economics, 7, 185–208.

Brand, J.E. and C.N. Halaby. 2006, "Regression and matching estimates of the effects of elite college attendance on educational and career achievement," Social Science Research, 35(3): 749–770.

Bryson, A. 2002, The union membership wage premium: an analysis using propensity score matching, Discussion Paper No. 530, Centre for Economic Performance, London.

Bryson, A., R. Dorsett and S. Purdon. 2002, The use of propensity score matching in the evaluation of labour market policies. Working Paper No. 4, Department for Work and Pensions.

Caiazza, S., A. F. Pozzolo and G. Trovato. 2016, "Bank efficiency measures, M&A decision and heterogeneity," Journal of Productivity Analaysis, 46, 25–41.

Caliendo, M. and S. Kopeinig. 2008, "Some Practical Guidance for the Implementation of Propensity Score Matching," Journal of Economic Surveys, 22, 1, 31-72.

Caliendo, M. 2006, Microeconometric Evaluation of Labour Market Policies, Lecture Notes in Economics and Mathematical Systems. Springer.

Coelli, T., S. Rahman and C. Thirtle. 2002, "Technical, allocative, cost and scale efficiencies in Bangladesh rice cultivation: a nonparametric approach," Journal of Agricultural Economics, 83, 607–626.

Davies, R. and S. Kim. 2003, Matching and the estimated impact of interlisting, Discussion Paper in Finance No. 2001-11, ISMA Centre, Reading.

Dehejia, R. und S. Wahba. 1999, "Causal effects in nonexperimental studies: reevaluation the evaluation of training programs," Journal of the American Statistical Association, 94, H. 448, S. 1053-1062.

Edet, O. G., E. E. Agbachom, and E. D. Uwah. 2019, "The effect of microcredit on technical efficiency of smallholder rice farmers in Ikot Ekpene Agricultural Zone, Akwa Ibom State, Nigeria," Global Journal of Agricultural Sciences, 18(1), 73-85.

Ham, J., X. Li and P. Reagan. 2004, Propensity score matching, a distance-based measure of migration, and the wage growth of young men, Working Paper, Department of Economics, Ohio State University.

Heckman, J.J., H. Ichimura and P.E. Todd. 1997, "Matching As An Econometric Evaluation Estimator: Evidence from Evaluating a Job Training Programme," Review of Economic Studies, 64, 605-654.

Heckman, J.J., H. Ichimura and P.E. Todd. 1998, "Matching as an Econometric Evaluation Estimator," Review of Economic Studies, 65, 261-294.

Heckman, J.J., R. J. LaLonde and J. Smith. 1999, The economics and econometrics of active labor market programs, in: Ashenfelter, O. and Card, D. E. (Hrsg.): Handbook of Labor Economics. Vol. 3. Amsterdam. S. 1865-2097.

Hitt, L. M. and F. X. Frei. 2002, "Do better customers utilize electronic distribution channels? The case of PC banking," Management Science, 48(6): 732-749.

Hossain, M., M. A. Malek, M. A. Hossain, M. H. Reza, and M. S. Ahmed. 2019, "Agricultural microcredit for tenant farmers: evidence from a field experiment in Bangladesh," American Journal of Agricultural Economics, 101(3), 692-709.

Iraizoz. B., I. Bardaji and M. Rapun. 2005, "The Spanish beef sector in the 1990s: impact of the BSE crisis on efficiency and profitability," Applied Economics, 37, 473–484.

Khan, A., A. Guttormsen and K.H. Roll. 2017, "Production risk of pangas (Pangasius hypophthalmus) fish farming," Aquaculture Economics and Management, 2: 192–208.

Khoshroo, A., R. Mulwa, A. Emrouznejad and B. Arabi. 2013, "A Non-parametric Data Envelopment Analysis Approach for Improving Energy Efficiency of Grape production," Energy Journal, 63:189–194.

Kotzian, P. 2009, "Productive efficiency and heterogeneity of health care systems: results of a measurement for OECD countries," Open Economy Journal, 2, 20–30.

Lawin, K. G., L. D., Tamini, and I. Bocoum. 2018, The Impact of Microcredit on Farms and Rural Household: A Literature Review of Experimental Studies, No. 2018s-07, CIRANO.

Parichatnon, S., K. Maichum and K.-C. Peng. 2018, "Measuring technical efficiency of Thai rubber production using the three-stage data envelopment analysis," Agricultural Econonics, 64: 227–240.

Perkins, S.M., W. Tu, M.G. Underhill, X. Zhou and M.D. Murray. 2000, "The use of propensity scores in pharmacoepidemiologic research," Pharmacoepidemiology and Drug Safety, 9(2): 93–101.

Rosenbaum, P. R. 1987, "Model-Based Direct Adjustment," Journal of the American Statistical Association, 82, 387–394.

Rosenbaum, P. R. 2004, "Design Sensitivity in Observational Studies," Biometrika, 91 (1), 153 - 164.

Rosenbaum, P. R. 2005, "Heterogeneity and Causality: Unit Heterogeneity and Design Sensitivity in Observational Studies," The American Statistician, 59: 147–152.

Rubin, D. B. and N. Thomas. 1992, "Affinely Invariant Matching Methods with Ellipsoidal Distributions," Annals of Statistics, 20 (2): 1079–1093.

Rubin, D. B. 1974, "Estimating Causal Effects of Treatments in Randomized and Nonrandomized Studies," Journal of Educational Psychology, 66 (5): 688–701.

Rubin, D. 1979, "Using multivariate matched sampling and regression adjustment to control bias in observational studies," Journal of the American Statistical Association, 74(366): 318–328.

Sianesi, B. 2001, Implementing Propensity Score Matching Estimators with STATA, UK Stata Users Group, VII Meeting London, May 2001.

Wadud, A. and B. White. 2000, "Farm household efficiency in Bangladesh: a comparison of stochastic frontier and DEA methods," Applied Economics, 32, 1665–1673.

Table 1: Frequency Distribution of Efficiency Index

	Microcredit Receiving Farms		Microcredit Non-receiving Farms	
Efficiency Cohort	**Number of Farms**	**Percentage of Farms**	**Number of Farms**	**Percentage of Farms**
0 - 50	1	0.89	4	2.59
50 – 60	4	2.22	8	4.74
60 - 70	12	7.11	13	7.76
70 - 80	36	21.78	38	23.28
80 - 90	97	58.89	63	37.93
90 - 100	15	9.11	39	23.71
Total	165	100	165	100

Table 2: Efficiency Comparisons of Microcredit Receiving and Non-receiving Farms, and Microcredit Program Impact

Measures	**Efficiency of Microcredit Receiving Farms**	**Efficiency of Microcredit Non-Receiving Farms**	**Coefficient of Variation**
Mean	83.57	81.94	1.392767
Standard Deviation	9.04	11.65	17.84001
Maximum	97.37	98.00	0.456034
Minimum	38	41.00	5.370431
Program Effect			
Mean Efficiency of Matched Treated		84.57	
Mean Efficiency of Matched Controlled		81.94	
Impact of Microcredit Program		1.63	

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.