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A Note on the Impact of Microcredit on Farm Income in Bangladesh : A Propensity Score Matching Approach

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Abstract *Propensity score matching (PSM) refers to the pairing of treatment and control units with similar values on the propensity score. Applying the PSM to a sample of 682 farms of which 450 are microcredit receivers and the rest 232 are microcredit non-receivers, the impact of microcredit on farm income is assessed. Results show a positive impact of microcredit on farm income indicating that the average income of microcredit receiving farms is 9.46 per cent higher than that of microcredit non-receiving farms. Thus this research can have strong bearing on policymaking and implementation in agriculture of developing economies like Bangladesh.*

Keywords: *Propensity Matching Score; Microcredit; Farm Income; Bangladesh*

JEL Codes: *Q1-Agriculture; C13 - Estimation*

1. Introduction

Microcredit is assumed likely to contribute both directly and indirectly to agricultural farm 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 equipments is of utmost importance.

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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.

As marginal and small farmers have little or no access to formal sources of credit, 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 food production and farm income.

Recently, 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, and hence raise farm income of marginal and small farmers. It has, therefore, become necessary to study the impact of microcredit on farm income. The present research is designed to achieve this objective. To the best of my knowledge, this research is first of its kind in Bangladesh.

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

2.1. Empirical Framework: Propensity Score Matching (PSM) Technique

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.

Matching is a widely-used non-experimental method of evaluation that can be used to estimate the average effect of a particular program.[3] 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. 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 program. Denote by the outcome (performance of farm) conditional on participation (P = 1) and by the outcome conditional on non-participation (P = 0).

The most common evaluation parameter of interest is the mean impact of treatment on the treated, $ATT=E(Y_1-Y_0\backslash p=1)=E[Y_1\backslash p=1)]-EY_0\backslash p=1]$, 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 $E[Y_1\backslash p=1)]$ are available from the program participants. An evaluator's 'classic problem' is to find, $E[Y_0\backslash p=1)]$ since data on non-participants enables one to identify $E[Y_0\backslash p=1)]$ only. So the difference between and $E[Y_1\backslash p=1)]$ and $E[Y_0\backslash p=1]$ 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 $S\backslash X$. Hence, after adjusting for observable differences, the mean of the potential outcome is the same for P = 1 and P = 0, $E[(Y_0\backslash p=1)=E[Y_0\backslash p=0,x)]-EY_0\backslash p=1]$. This permits the use of matched non-participating farms to measure how the group of participating farms would have performed, had they not participated.

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.

3 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. 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. 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.

Table 1: Logistic Regression for Propensity Score [2] and Program 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
Maximized value of the log-likelihood function		-442.7508
Program Effect		
Mean Income of Matched Treated		18397.40
Mean Income of Matched Controlled		16656.30
Impact of Microcredit Program		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 = .22943, Pseudo-R-Squared = .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 program for agriculture are shown at the end of Table 1. The microcredit program 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.

4. Conclusions

This study aims to assess the impact of microcredit on farm income. We apply the propensity score matching (PSM) technique to a sample of 682 farms of which 450 are microcredit receivers and the rest 232 are microcredit non-receivers. Results reveal that microcredit contributes to generation of income of farms. The average income of microcredit receiving farms is 9.46 per cent higher than that of microcredit non-receiving farms. Based on the results, 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 an increase in agricultural farm output and income in Bangladesh.

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