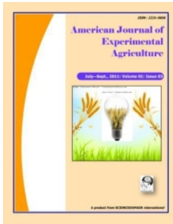

American Journal of Experimental Agriculture
2(3): 502-515, 2012

SCIENCEDOMAIN *international*
www.sciencedomain.org

SCIENCEDOMAIN

Women Participation in Microcredit and Its Impact on Income: A Study of Small-Scale Businesses in the Central Region of Ghana

Dadson Awunyo-Vitor[1*], Vincent Abankwah[2] and Julius Kwesi Kum Kwansah[3]

[1]Department of Agricultural Economics, Agribusiness and Extension, Kwame Nkrumah University of Science and Technology, Kumasi, Ghana.
[2]Department of Agricultural Economics and Extension Education, University of Education, Winneba, Ghana.
[3]Ghana Education Service, Agona Nsabah, Ghana.

Authors' contributions

This work was carried out in collaboration with all authors. DAV designed the study, performed the statistical analysis and wrote the first draft of the manuscript. VA and JKKK managed the data collection and the literature searches. Vincent reorganized and summarized the manuscript and all authors read and approved the final manuscript.

Research Article

Received 1st February 2012
Accepted 30th March 2012
Online Ready 28th June 2012

ABSTRACT

Aim: To examine women participation in microcredit and its impact on business income.
Study Design: Cross-sectional data.
Place and Duration of Study: The study was carried out from March 1 to 30, 2011 in five districts from the Central Region of Ghana which is basically agrarian.
Methodology: A multistage randomized sampling method was used in selecting 300 business women from the five districts: Agona West Municipality; Cape Coast Metropolis; Efutu Municipality; Mfantsiman Municipality and Upper Denkyira East District. Structured questionnaire and interview schedule were used to elicit information from the respondents. Information sought bordered on business income, the socio-economic characteristics of the respondents and other factors that influence participation in microcredit. Analysis of data was carried out using propensity score matching (PSM) approach.
Results: Results revealed that number of years in formal education, satisfaction of

**Corresponding author: Email: Awunyo-vitor.ksb@knust.edu.gh;*

application procedures, membership to business associations, amount of savings with financial institutions, and the satisfaction of interest charges are factors that positively influence women's likelihood of participating in microcredit programmes. The PSM results showed that women operating small businesses with microcredit had statistically significant higher income compared with their non-microcredit participating counterpart.

Conclusion: It is, therefore, concluded that formal schooling, satisfaction with lending procedures and interest as well as amount of money saved with the micro finance institution influence their participation in the micro credit programme. Also microcredit provides a means for increasing income of women in small scale businesses. Based on the PSM results women in small businesses should be encouraged to participate in microcredit as it significantly increases their income levels.

Keywords: Microcredit; small businesses; propensity score matching; counterfactual; Logit.

1. INTRODUCTION

Microfinance, according to Otero (1999) is "the provision of financial services to low income poor and very poor self-employed people". These financial services according to Ledgerwood (1999) generally include savings and credit but can also include other financial services such as insurance and payment services. Microfinance over the years has been considered to be one of the most effective and flexible strategies in the fight against global poverty. It is said to be sustainable and can be implemented on the massive scale necessary to respond to urgent needs of those living on less than $1 a day, the World's poorest (Ghana Microfinance Institution Network (GHAMFIN), 2003). It has been seen to be promoting economic growth since loans given are supposedly used to invest in micro business.

Small and Micro Enterprises (SMEs) provide a safe net for women entrepreneurs in Ghana. Excellent performance of this sector hold key to poverty reduction as it would lead to creation of job and income generation. However their key challenge is access to finance. SMEs' access to credit is assumed to improve their performance and create jobs with consequent decrease in poverty level. To meet the credit need of SMEs, Bank of Ghana implemented several policy initiatives to improve access to finance by small scale business operators as it is difficult for most of them to access credit from formal financial institutions. This has led to emergence of Micro-Credit Institutions that lend through groups to overcome collateral problems (Hossain, 1988; Mosley, 1996). Zeller et al. (2002) and Ghalak, (1999) identified this approach as having an important feature of associating creditworthiness with membership of a group or cooperative with a common aim of doing business since peer pressure for loan repayment and membership restrictions provides enough collateral for the financial institutions.

According to GHAMFIN (2003), there are more than 233 Micro-Finance Institutions (MFIs) operating in Ghana. Some are banking institutions, Non-Governmental Organizations (NGOs), Christian Organizations and Non-banking Financial Institutions. However, there have been concerns by many authors, Paxton et al. (2000) and Onyuma et al. (2005), on whether credit from these micro finance institutions does not worsen the plight of small businesses as their lending interest rate are seemingly higher. It is on this ground that this study is organized to identify factors which influence participation in micro credit programme and the impact of microcredit programmes on performance of small scale businesses owned by women in the Central region of Ghana.

Findings from this study would not only clarify the suspicion of people as to whether micro credit is beneficial to subscribers but would also equip the micro finance institutions and other NGOs to streamline their activities to make microfinance more beneficial to their clients. The choice of women for the study is in line with the observation made by the International Monetary Fund (IMF, 2008) on the fact that women are more credit constrained than their male counterparts. This has implication for their businesses and one way to develop policy to ease their credit constraint is to understand the nature of factors that influence access to credit and the impact of credit on their business performance. Hence this study focuses on women in small scale business specifically women who are engaged in food processing and petty trading in the Central Region of Ghana which is basically agrarian.

1.1 Impact Evaluation Methods

The literature on impact evaluation methods and practices is large, however, some authors (Duflo et al., 2008; Ravallion, 2008; Blundell and Dias, 2000) present very useful overviews. Also, Khandker et al. (2010) have discussed in detail different methods that are applicable for impact evaluation and the data needed for each type. In their methodological review, they stress the need to address the fundamental question of the missing counterfactual data in impact evaluation in a non-experimental context such as assessing impact of financial services on performance indicators. With cross-sectional data from observational study, they discussed the use of Propensity Score Matching (PSM) approach and pointed out that this method can be used under conditional independence and common support assumptions (Khandker et al., 2010). The main thrust of these assumptions is that all factors influencing participation are observable and individuals with similar characteristics have an equal chance of belonging to either group (participants and non-participants). A number of studies used this method to assess impact of interventions which deal with selection of participants from a pool of all interested individuals.

Others used PSM in impact studies which did not deal with an intervention or programme. For example, Owusu and Abdulai (2009) used this method to evaluate impact of non-farm income on food security and poverty in rural Ghana. In their study, there was no intervention; however, the authors argue that participation in non-farm activities requires decision by the individual, which is influenced by certain individual factors which placed them in either group. In addition these factors are observable. In a related study, Becerril and Abdulai (2010) examined impact of maize varieties on farm output and income levels in Mexico. A number of maize varieties were released earlier and some farmers adopted it while others did not. Therefore, this study was not in the confines of a programme or intervention. In both studies, the basis for the use of PSM is that the factors which influence selection into participation (treated) and non-participation (untreated) groups are observable.

Mutua and Oyugi (2006) evaluated access to financial services and poverty reduction in rural Kenya using descriptive analysis. The study looked at the role access to financial services can play in addressing poverty and its related problems, especially in the rural areas. They observed a strong link between access to finance and poverty reduction. Owuor (2009) empirically examined the impact of micro-finance on smallholder farmers in Kenya using Propensity Score Matching. He found that smallholders' participation in micro-finance credit (MFC) improves their income by a range of between US$ 200.00 and US$ 260.00 per hectare in a single production period. However, participation in the Micro-Finance Credit

(MFC) among smallholder farmers was constrained by low literacy levels, gender, differentials in asset endowment, poor road infrastructure and maintenance of indigenous group structures.

2. METHODOLOGY

2.1 Sampling Procedure

The study covered five districts in the Central Region of Ghana namely: Agona West Municipality; Cape Coast Metropolis; Effutu Municipality; Mfantsiman Municipality and Upper Denkyira East District. These districts were purposively selected because of their relatively high level of economic activities and presence of financial institutions that provide microcredit to women in small scale businesses. A multi-stage random sampling methodology was used to arrive at a total sample size of 300 women who are in small businesses.

The total number of respondents' was estimated using estimation method given by Yamane (1967) as

$$n = N/1 + N(e)^2$$

Where n is the sample size; e = error level; e = 1 – confidence level and N is the estimated total population of the target group. Assuming 95% confidence level, e = 0.05 and an estimated 1,300 registered women in small businesses in the five districts; a sample size of 300 women in small businesses was selected for the study.

In the first stage of the sampling procedure, a purposive sample of five districts was made, while in the second stage a stratified random sampling of 3 credit beneficiary groups and 3 non-credit beneficiary groups per district were then selected. Finally, in stage three, 10 members from each of the groups were randomly selected, making a total of 60 respondents (1 x 6 x 10) per district. The total respondents selected from the 5 district were 300 comprising 150 microcredit participating women and 150 non-microcredit participating women. The list of groups and members were obtained from the local branches of financial institutions operating microcredit scheme in the study area. A structured questionnaire was used to collect data from the sampled respondents in March, 2011.

2.2 Conceptual Framework and Analytical Approach

Available literature on the causal relationship between access to financial services (microcredit) and its impact on poverty alleviation is mostly observational from a few case studies (Mutua and Oyugi, 2006). Taken participation in micro credit as a treatment, then those who participated are referred to as treated and non-participants are refereed to untreated or control group.

In trying to study the impact of microfinance programme on a group of microcredit participants (treatment group) in comparison with a group of non-microcredit participants (control group), researchers have had to contend with two estimation problems of selection bias. This is because to evaluate the impact of a treatment such as microcredit participation on performance indicators it is necessary to draw a counterfactual scenario about the performance indicators of the treated group (participants). The counterfactual performance indicators of the treated would be determined in absence of the treatment. The counterfactual indicators would then be compared with the performance level of the treated when they participate in microcredit in order to evaluate the impact of the treatment on the performance indicators. For the microcredit participants (treated group) their counterfactual would be the performance level in the absence of microcredit. While for the non-microcredit participants (control or untreated group), their counterfactual would be the level of performance when they participate in microcredit. However, the challenge here is that it is difficult to assess counterfactuals, thus some studies used the performance level of the control group as counterfactual. This has been proved to result in bias estimates of the effect of the treatment. Thus to eliminate selection bias, there is the need to compare the performance levels of treated and control groups which are statistically identical (Rosenbaum and Rubin, 1983; Khandker et al., 2010). Rosenbaum and Rubin (1983) suggest the use of Propensity Score Matching (PSM) approach to deal with selection bias. The PSM approach is based on the idea that by matching the outcome (performance levels) of treatment and control respondents who are similar in observable characteristics, selection bias would be eliminated. The PSM is used to correct for the estimation of effects of the programme controlling for the existence of these confounding factors based on the idea that the bias is reduced when the comparison is performed using treated and untreated or control respondents who are as similar as possible. Based on the foregoing discussion, the PSM was chosen as a proven tool of analysis for this study.

The PSM approach follows two steps, first binary model is used to estimate the probability of participating or being treated (propensity score) on observable characteristics. Propensity score is a conditional probability estimator and any discrete choice model such as logit or probit can be used as they yield similar results (Caliendo and Kopeinig, 2008). In this study logit model is used, which is specified as:

$$P(X) = P(D = 1|X) = F(\beta_1 X_1 + \cdots \beta_i X_i) = F(X\beta) = e^{X\beta} \tag{1}$$

Where $F(.)$ denote response probability which strictly ranges between zero and one and X represents all observable characteristics (Covariates) which influence treatment (participation in microcredit programme), β is the parameter of interest to be estimated.

This model enables us to predict the probability (propensity score) of participation in microcredit programme. Given that the propensity score is a balancing score, the probability of being treated conditional on X will lead to distribution of respondents' covariates X such that these covariates X will be the same for treated and control groups.

Assuming all information relevant to microcredit programme participation and income are observable then, the propensity score will produce valid matches which can be used to estimate, impact of microcredit on income at the second stage of the analysis. This is done by matching the two groups of respondents on the basis of the predicted propensity score as follows:

$$ATT = E_{P(X)}\{(E(Y_1|D = 1, P(X)) - E(Y_0|D = 0, P(X))\} \tag{2}$$

Where ATT represents Average Treatment effect on the Treated group.

$E_{P(X)}$ denotes the expectation with respect to the distribution of propensity score in the entire population and D denotes microcredit participation indicator which is equal to one (1) if a woman participated in microcredit and zero (0) if otherwise. The estimation of ATT clearly depends on the counterfactual levels or the performance level i.e the income of the two groups: treated and control for $(Y_1|D=1)$ and $(Y_0|D=0)\}$ respectively as explained above.

Three different matching algorithms were used which involve trade-offs in terms of bias and efficiency to match treated and untreated respondents. These are:

Nearest Neighbour Matching (NNM), this method selects the control group with the smallest distance in propensity score to the treated group. Generally, this is done with replacement and it works well once the distribution of the propensity score of both groups (control and treated) are similar (Backer and Ichino, 2002)

Radius Matching (RM) or Calliper involves all neighbours with a maximum propensity score distance. This is normally defined *a* priori and it corresponds to common support assumption. Radius matching also helps to avoid poor matches which may arise through matching too distant neighbours (Smith and Todd, 2005). Radius matching is where an individual from the control group is chosen as a matching partner for a participant that lies within the specified radius in terms of propensity score.

Kernel-Based Matching (KM) was recommended by Heckman et al. (1997). This is non-parametric estimator that include all respondents of the underlying sample of control group and weight more distant observed characteristics among both group (control and treated) down. Hence it indicate lower variance, nevertheless Caliendo and Kopeinig (2008) noted that poorer matches could be obtained. The Kernel –based estimator of the ATT describes the mean difference in outcome while the matched outcome is given by Kernel-weighted average of the outcome of control group of respondents. In the case of Kernel Matching (KM), each participant is matched with a weighted average of all controls with weights that are inversely proportional to the distance between the propensity scores of participants and controls.

In considering quasi-experimental design of the women participation in micro credit programme, it might be possible that unobservable factors like women intrinsic motivation and specific ability as well as preferences had effect on their participation decision. This could cause the result of the PSM or the impact of participation to differ as a result of the deviations from the underlying conditional independence assumption due to the presence of hidden bias.

Therefore it is important to test the presence of unobserved variable which could cause hidden bias. This can be done by using sensitivity analysis following bounding approach (Rosenbaum, 2002). By complementing the logit model used to estimate the propensity score (Equation 1) by a vector U containing all unobservable variables and their effect on the probability of participation captured by γ as follows:

$$P(X) = P(D=1|X) = F(\beta X + \gamma\mu) = e^{\beta X+\gamma\mu} \tag{3}$$

Assuming $i\&j$ are matched pairs of individuals within each group (treated and untreated) the probability of being treated can be presented as:

$$\frac{P_i}{1-P_i} \text{ and } \frac{P_j}{1-P_j} \tag{4}$$

$$= \frac{\frac{P_i}{1-P_i}}{\frac{P_j}{1-P_j}} = \frac{P_i(1-P_i)}{P_j(1-P_j)} = \frac{\exp(\beta x_i + \gamma u_i)}{\exp(\beta x_j + \gamma u_j)}. \tag{5}$$

With identical observed covariate for both individuals x will cancel out such that

$$\frac{\exp(\beta x_i + \gamma u_i)}{\exp(\beta x_j + \gamma u_j)} = exp\{\gamma(u_i - u_j)\} = e^{\gamma(u_i - u_j)} \tag{6}$$

It can be seen that despite the same covariate for both pairs they still differ in their odd of participating in micro credit programme by a parameter γ and differences in their unobserved covariates, $u_i - u_j$. However, if there are no difference in unobserved variables or if unobserved variable have no influence on the probability of participation then $u_i = u_j$

Therefore, as long as there is no difference between the two individuals or if the unobserved variable exerted no influence on the probability of participation the relative odd ratio become one and selection process is random. $e^{\gamma(u_i - u_j)} = e^{\gamma} = 1$. Following Rosenbaum (2002) the following bounds on the odd ratio of the participation probability of both individual are applied.

$$\frac{1}{e^{\gamma}} \le \frac{P_i(1-P_i)}{P_j(1-P_j)} \le e^{\gamma} \tag{7}$$

Both groups have the same probability of participation, provided that they are identical in covariates X only if e^{γ}=1. Consequently there will be no selection bias on unobservable characteristics. However, if $e^{\gamma} = 2$, then one of the matched pairs may be twice as likely to participate as the other pair or agent (Rosenbaum, 2002).

Hence e^{γ} is used to measure the degree of departure from the similarity that may lead to a hidden bias (Rosenbaum, 2002).

According to Rosenbaum (2002), an appropriate control strategy of hidden bias is to examine the sensitivity of significance levels by calculating several values of $\boldsymbol{e^{\gamma}}$ bounds on the significance level. In this case the null hypothesis is that participation has no effect on the potential outcomes. The sensitivity analysis helps to identify the critical impact level of the unobservable at which the inference or conclusion about the treatment effect will be undermined. This is indicated by the loss of significance (Diprete and Gangl, 2004). In this study the sensitivity of significance levels was evaluated following Rosenbaum (2002).

3. RESULTS AND DISCUSSION

The results of the study have been presented in two sections. In the first section, the result of logit model was presented and discussed. In the second section, the impact of the micro credit on business income of the women is presented.

3.1 Determinants of Microcredit Participation

In accordance to chosen characteristics used to capture observable relevant differences between microcredit participating women and non-microcredit participating women, Table 1 reports the results from the logit model, with the estimated coefficients expressed in terms of odds. The logit regression gave a Pseudo (McFadden) R–squared of about 0.62 which implies that all the explanatory variables included in the model are able to explain about 62 percent of the probability of participating in microcredit programme by the women. The overall model is statistically significant at a P-Value of 0.000. Hence, the chosen observable characteristics adequately explain the probability of participation.

Table 1. Logit model predicting probability of microcredit participation

Dependent variable: Participation Covariates	**Odds ratio**	**t- Statistic**	**Marginal effects**
Age	1.048	1.21	0.011
Number of years of schooling	1.012**	2.7	0.004
Perception of application procedures 1=satisfactory, 0=otherwise	1.843***	3.6	0.147
Knowledge of different micro credit sources ,1= have knowledge of other source of credit, 0= otherwise	1.006	0.75	0.002
Membership to economic associations,1= member, 0 otherwise	1.012**	2.8	0.004
Savings with financial institution (GH¢)	2.264***	5.6	0.182
Type of business 1= petty trading 0= Otherwise	1.256	1.12	0.054
Perception of level of interest rate 1= high 0= Otherwise	0.208***	-3.6	-0.371
Distance from residence to financial institution (km)	0.996	-1.2	-0.001
Number of obs = 300 LR chi2(9) = 96.89 Prob > chi2 = 0.0000 Log likelihood = -344.64863 Pseudo R^2 = 0.6232			

*The asterisks denote level of significance *** Significant at 1%; ** Significant at 5%;*
** Significant at 10%*
Source: Survey data, 2011

Examining single observables, it is shown that individual socio-economic characteristics are significant in the participation model. Each increase in years of schooling is associated with a 1.01 odds of participation. Considering a marginal change in the number of years of schooling the probability of participation would increase by 0.4%. It is, therefore, established that higher education fosters participation in microcredit. Perception of application procedure yields even a higher impact as long as business women perceive application procedure to be less cumbersome, probability of participation increases to 14.7%. Women who see application procedure as bureaucratic are less likely to participate in microcredit. Likewise, the probability of a woman participating in microcredit programme would increase by 0.4% when individual belongs to economic association. In case the individual savings with financial institution increases by GH¢1.00, the probability of participation would increase by 18.2%. The marginal effect is about 37% higher for individuals who perceive interest rate to be high.

3.2 Impact of Microcredit on Business Income

A visual presentation of the density distributions of the estimated propensity scores for the two groups is shown in Figs. 1a, 1b and 1c. These histograms illustrate the number of respondents who are on microcredit support and those off microcredit support. It can be seen that the common support condition is satisfied. There is substantial overlap in the distribution of the propensity scores of both microcredit (treated) group and non-microcredit (untreated) group of the women'. The bottom halves of the histograms show the propensity scores distribution for the non-microcredit group while the upper halves refer to that of the microcredit group.

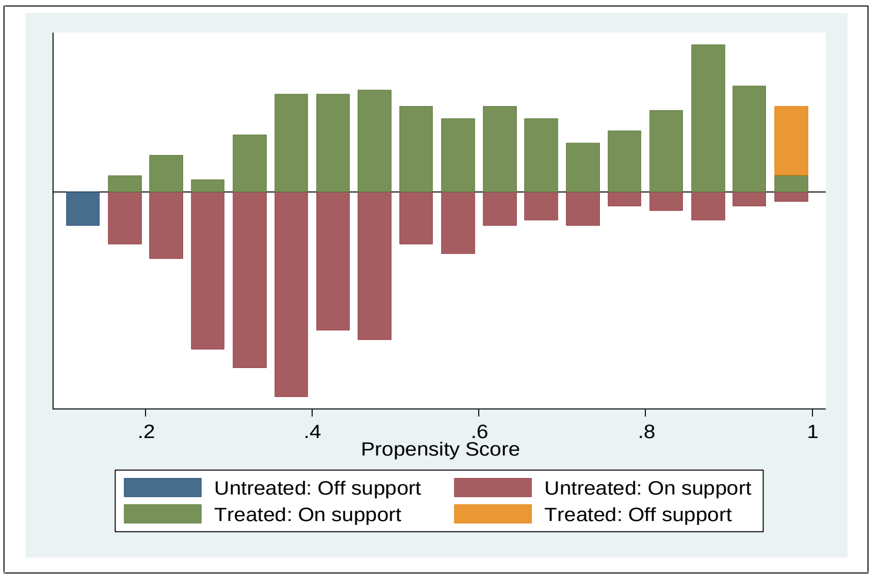

Fig. 1a. Density distribution of propensity scores using nearest neighbor

The results of the treatment effects (ATT) for the microcredit participating on income are estimated using all the three matching algorithm shown in Table 2. The nearest neighbour estimate of the ATT of microcredit on income level of the respondents recorded an increase of GH¢85. This increase is statistically different from zero. This implies that women who participated in microcredit have significantly increased their earnings by GH¢85-compared to non-microcredit women for a loan cycle of 3 months. In the case of calliper or radius matching we consider neighbours with a calliper of 0.01. The results show GH¢79 significant increase in income as a result of women participation in microcredit. With regards to Kernel base matching algorithm each treated respondents (microcredit participants) is matched with a weighted average of all untreated respondents (non-microcredit participants) with weights that are inversely proportional to the distance between the propensity score of the participants and non-participants. In this study we used a smoothening parameter of 0.06 as recommended by Silverman (1986). The average treatment effect on the treated (ATT) revealed increase in income by GH¢82 which is statistically different from zero at 1% significant level. All the matching techniques produced consistent estimates of the treatment effects of microcredit participation on income of the women in small businesses.

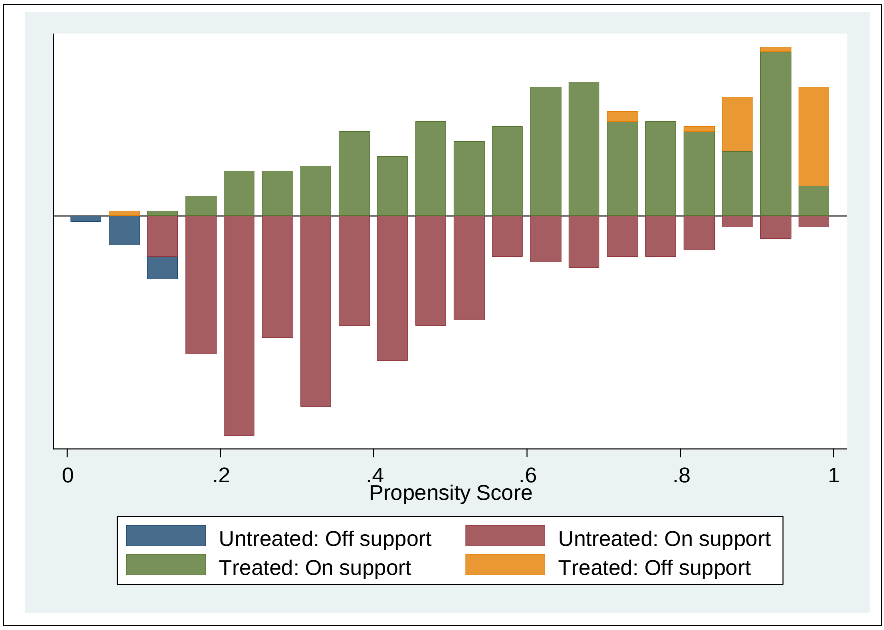

Fig.1b. Density distribution of propensity scores using calliper or radius

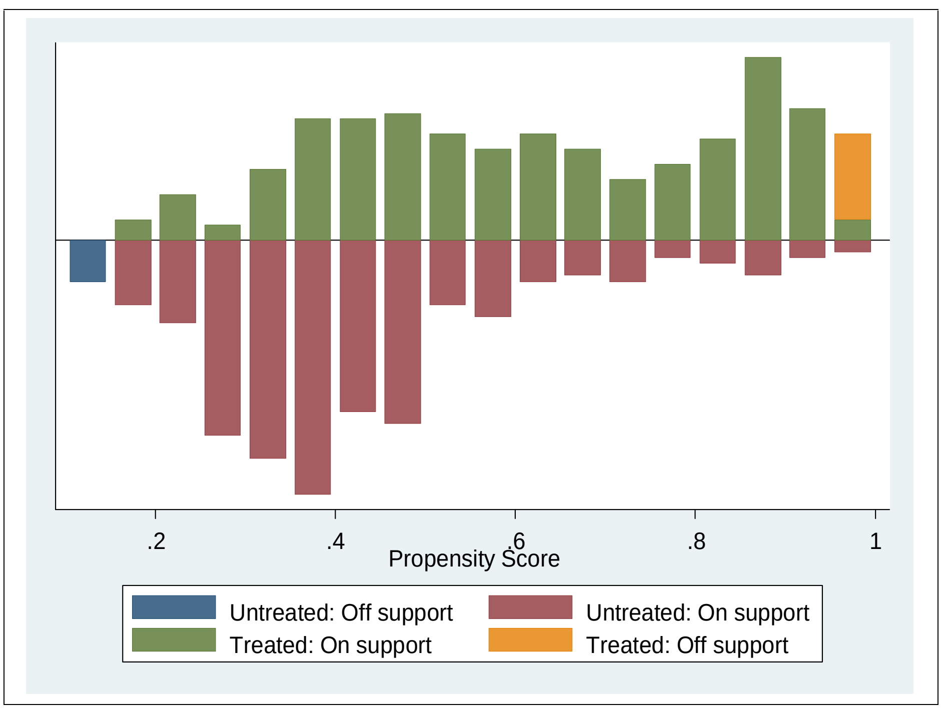

Fig. 1c. Density distribution of propensity scores using kernel based matching

Table 3 presents results of sensitivity analysis. Here, five different values of e^{γ}bounds were used to test the robustness of the significance level in the PSM. The null hypothesis of no effect of participation on income was tested using the three introduced matching algorithms. Results of robustness produced by Rosenbaum's bounds for the three matching algorithm are quite similar. Nearest neighbour matching produces the most robust treatment effect estimates with respect to hidden bias.

When $e^{\gamma} = 1$ the result of the PSM is still significant at 1% for nearest neigbour matching algorithm and at 5% significant level for capilar and Kennel matching algorithm with the p-values of 0.0072, 0.0255 and 0.01200 respectively.

Table 2. Estimated impact of microcredit participation on outcome variable (income)

Outcomes & number of observations	Average Treatment Effect (ATE)	Average Treatment effect on untreated(ATU)	Average Treatment effect on the treated (ATT)
Nearest Neighbour Matching (NNM)			
Income	190.826	.642	85.184*** (4.93)
N0. of observation	118	125	
Radius matching with a calliper of 0.01			
Income	192.51861	113.095255	79.42336*** (3.17)
N0. of observation	121	110	
Kernel-based matching (KBM) with smoothening parameter of 0.06			
Income	192.083	109.502	82.5813*** (3.02)
N0. Of observation	118	125	

*Note t-statistics are in parenthesis *** denotes significant at 1% ** denotes significant at 5% * denotes significant at 10%. No. of observation represents individuals in microcredit participating group that match individuals in non-microcredit participating group*
Source: calculated from survey data, 2011

Table 3. Sensitivity analysis with Rosenbaum's bounds on probability values on income

	Upper bounds on the significance level for different values of e^{γ}				
	e^{γ}=1	**e^{γ} =1.25**	**e^{γ} =1.5**	**e^{γ} =1.75**	**e^{γ} =2**
Using the single closest neighbour					
Income	0.0001	0.0072	0.0871	0.327	0.6324
Using all neighbours within a calliper of 0.01					
Income	0.0005	0.0255	0.1884	0.505	0.785
Using a biweight kernel function and a smoothing parameter of 0.06					
Income	0.0001	0.012	0.1254	0.4131	0.7202

Source: Calculated from survey data, 2011

However with $e^{\gamma} = 1.5$ only nearest neighbour matching algortithm is significant at 10% level of significance the rest are not significant.

Thus if matched pairs differ in odd of participating in micro credit program by 1.25 ($e^{\gamma} = 1.25$) in unobservable characteristics, the impact of participation on income would still be significant at a level of 5%.

The estimated treatment effect on income is sensitive to hidden bias at rather a smaller unobservable impact level of ($e^{\gamma} = 1.5$). Nevertheless, it has to be considered that these sensitivity results are worst-case scenarios, even though they indicate information about uncertainty within the matching estimators of treatment effects (Rosenbaum, 2002).

4. CONCLUSION AND RECOMMENDATION

From the logistic regression results, number of years in formal education, satisfaction of application procedures, membership to business associations, amount of saved with micro finance institutions savings and the satisfaction of interest charges are factors that positively influence women's likelihood of participating microcredit programme. The results of the PSM showed that women operating small scale businesses who participated in microcredit had statistically significant higher income compared with their non-microcredit participating women. It is, therefore, concluded that microcredit provides a means for increasing income of women in small scale businesses.

Giving the relevance of economic associations in driving participation in micro credit programme, it is recommended that the existing associations be strengthened and sustained and new ones formed. Also, Governmental and Non-Governmental Organisations that work to empower women should adopt formation of economic associations in delivering their interventions. This will ensure that women in small scale businesses participate in microcredit programme for improved income levels.

Women who are not in associations are encouraged to join existing ones or form their own so as to improve their chances of accessing microcredit from the microfinance institutions. The perceptions of the women regarding the lending procedure and interest influence their participation in the micro credit programme. Therefore the need to create awareness of what is required to access credit through public education is important to improve access to microcredit by the women.

It is therefore recommended that the microfinance institutions should come out with an educational package that will help give the right information to women regarding what micro credit packages they offer and the condition for access. Giving that savings influence participation in microcredit programme, it is recommended that all women engaged in small businesses should endeavour to make some savings with the microfinance institution to improve their participation in their credit programme. Based on the PSM results women in small businesses should be encouraged to participate in microcredit as it significantly increases their income levels. This is because increased income levels have implication for women empowerment which is critical for sustainable livelihoods development.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

REFERENCES

Becerril, J., Abdulai, A. (2010). The impact of improved maize varieties on poverty in Mexico: A propensity score marching approach. World Development, 38(7), 1024–1035.

Becker, S.O., Ichino, A. (2002). Estimation of average participation effects based on Propensity Scores. The Stata Journal, 2(4), 358-377.

Blundell, R., Dias, M.C., (2000). Evaluation methods for non-experimental data. Fiscal Studies, 21(4), 427–468.

Caliendo, M., Kopeinig, S. (2008). Some practical guidance for the implementation of propensity score matching. Journal of Economic Surveys, 22(1), 31-72.

DiPrete, T., Gangl, M. (2004). Assessing bias in the estimation of causal effects: Rosenbaum bounds on matching estimators and instrumental variables estimation with imperfect instruments. Sociological Methodology, 35, 271-310.

Duflo, E., Glennerster, R., Kremer, M. (2008). Using randomization in development economics research: A toolkit in Schultz, T.P., Strauss J.A (Eds), Handbook of Development Economics, Volume 4, Elsevier.

Ghana Microfinance Institutions Network (GHAMFIN). (2003). "Census of micro credit ngos, community-based organizations and self help groups in Ghana," Accra, GHAMFIN, draft report prepared by Asamoah & Williams Consulting, Kumasi-Ghana.

Ghana Statistical Service (GSS). (2008). Report on the fifth round of Ghana Livings Standard Survey (GLSS 5). Accra, Ghana.

Ghatak, M. (1999). Group lending, local information and peer selection. Journal of Development Economics, 60, 27-50.

Heckman, J., Ichimura, H., Todd, P. (1997). Matching as an econometric evaluation estimator: evidence from evaluating a job training programme. Review of Economic Studies, 64, 605-654.

Hossain, M. (1988). Credit for alleviation of rural poverty. The grameen bank in bangladesh (research report no. 65), Washington: International food policy research institute in collaboration with the Bangladesh institute of development studies.

Khandker, S.R., Koolwal G.B., Samad, H.A. (2010). Hand book on impact evaluation: quantitative methods and practices: quantitative methods and practices. The World Bank, Washington D.C.

Ledgerwood, J. (1999). Microfinance handbook: an institutional and financial perspective. Washington D.C: World Bank.

Mosley, P. (1996). Credit for low-income groups: an analytical framework (working paper on finance for low-income groups no. 1). Rouledge, London.

Mutua, J.M., Oyugi, L.N. (2006). Access to financial services and poverty reduction in rural Kenya (NEPRU working paper No. 108). Retrieved on 20 November 2011, from www.nepru.org.na/index.php?id=127.

Onyuma, S., Ouma, S.A. (2005). Myths of microfinance as a panacea for poverty eradication and women empowerment. Savings & Development Quarterly, 2, 119-222.

Otero, M. (1999). Bringing development back into microfinance, Retrived 14 July 2006, from http://www.accion.org/file_download.asp?f=8.

Owuor, G. (2009). Is micro-finance achieving its goal among smallholder farmers in Africa? Empirical evidence from Kenya using propensity score matching: paper presented at the xxv11 international conference of agricultural economists, Beijing, China. August, 16-22, 2009.

Owusu, V., Abdulai, A. (2009). Non-farm work and food security among farm households in northern Ghana. Retrieved on December 2010, from www.pegnet.ifw-kiel.de/activities/research/.../non-farm northern-Ghana.

Paxton, J., Graham, D., Thraen, C. (2000). Modeling group loan repayment behavior: new insights from Burkina Faso. Economic Development and Cultural Change, 48(3), 639-655.

Ravallion, M. (2008). Evaluating anti-poverty programmes. Handbook of Development Economics, 4, Amsterdam.

Rosenbaum, P. (2002). Observational Studies. New York, Springer.

Rosenbaum, P., Rubin, D. (1983). The central role of the propensity score in observational studies for causal effects. Biometrika, 70, 41-50.

Silverman, B.W. (1986). Density estimation for statistics and data analysis. London, UK Chapman & Hall.

Smith, J., Todd, P. (2005). Does matching overcome lalonde's critique of non experimental estimators? Journal of Econometrics, 125(2), 305-353.

Yamane, T. (1967*).* Statistics: An Introductory Analysis*,* 2nd Ed., New York: Harper and Row.

Zeller, M., Sharma, M., Ahmed, A., Rashid, S. (2002). Group-based financial institutions for the rural poor in Bangladesh: An institutional-and household-level analysis. (Research report No. 120). Washington, D.C.: International Food Policy Research Institute.