Journal of Poverty, Investment and Development www.iiste.org
ISSN 2422-846X An International Peer-reviewed Journal
Vol.46, 2018

Impact of Microfinance on Poverty Reduction in Ethiopia: Case of Omo Microfinance in Hosana Town

Birhanu Hankamo Kintamo (MSc.)
Department of economics, Wolaita Sodo University, Ethiopia

Abstract
Poverty is a harsh and undesired phenomenon in mankind. Reducing, if possible eradicating poverty is unquestionable. Microfinance programs have been considered as an instrument in poverty reduction in recent development agenda. The main objective of this study was to investigate empirically impact of Omo microfinance institutions on poverty reduction at household level referencing Wachamo surrounding Omo microfinance institution. Mainly primary data was collected through structured questionnaire from 200 households by selecting 90 OMFIs participants and 110 non-OMFI participants from two sub cities using random sampling methods. Propensity score matching (PSM) methods was used to assess the impact of OMFI on household income, expenditure, saving and asset accumulation value. The estimation ATT results from PSM output show that participation in OMFI had brought significant impact on household income, saving and aggregate expenditure. Even if, intervention brought insignificant impacts on asset accumulation value it enable the participant to own home asset. Furthermore, sensitivity analysis tested on estimated ATT result in which it shows that effect of MFIs was insensitive to unobservable selection bias; even the two group allowed to differ in their odds of being treated up to 220% in terms of unobserved in which implying that being pure effect of program intervention. Thereby, improving living standard of participant and as far as ATT result was the only effect of intervention, thus microfinance intervention reduce poverty at household level. It can be recommended that, importance of microfinance in poverty reduction is of immense benefit to the participant households in study areas. Therefore, there is the need to help sustain it and help its growth as its role to the development of the Hosanna town and the country at large is very good.
Keywords: Microfinance, poverty reduction, ATT and propensity score matching

1. INTRODUCTION

1.1. Background of the Study

Poverty remains a global problem of huge proportions of populations in world; it haunts the lives of billions of people around the world which needs a great attention to reduce it (WDR, 2000/2001). Besides of its broad, multifaceted and multidimensional concept it involved in the economical, social, political and environmental well-being of the people (WB, 2002). In fact that, lack of income followed by low living standard. According to World Bank (2004), poverty is the manifestation of developing world Eradicating or possible reducing it was the greatest single challenge in low and middle income countries. Thus**,** Ethiopia is one of the poorest countries and poverty cases a multi-dimensional problem (Bisrat, 2011). Though provision of financial services to poor people that have been excluded from the formal financial sector for so long, microfinance aims at poverty alleviation. In supporting this idea, Wolday (2001) states that microfinance was one of strategy that contributes to reduce poverty and also it is an important tool in the poverty eradication programs. Also in Ethiopia these institutions aimed at poverty alleviation by targeting specific groups particularly poor (Wolday, 2001). After introduction of proclamations No. 40/1996, one of the MFI established in Ethiopia is Omo microfinance institution S. C OMFIs (Deribie et.al, 2013). Today it operates in all zones in the SNNPRs through provision of financial and non-financial services to poor (OMFI, 2013). So therefore, this study conducted in which OMFIs operating in Hosana town to analyze impact of its intervention at household level.

1.2. Statement of the problem

In addition to, it's broad, multifaceted and multidimensional poverty involved in economical, social, political and environmental well-being of the people (WB, 2002). Whereas, developing countries were developed their own national poverty reduction strategies (UNDP, 2003). Thus, microfinance institutions were one of the strategies that help to reduce poverty (Wolday, 2001). However, formal MFIs started in Ethiopia since 1996, provides financial and non-financial service to low income (Deribie et.al, 2013). Accordingly, studies by Asmelash, 2003 and Mebratu, 2008 investigated empirically impact of microfinance institutions in poverty reduction. Their finding reveals that microfinance brought positive and significant impact on the living standard of participant. Meanwhile, the studies report the current expenditure status of the participants, but give no ideas on the condition of those clients before joining the program. Although, according to Mebratu (2008) poverty in Ethiopia were problems in both rural and urban, but in urban increase in number due to rural-urban migration at least by the amount of the new comers whose needs are not accommodated, in addition to deepening poverty of the existing urban poor. Moreover, study by Bisrat (2011) demonstrates positive impact of microfinance on its participant but not estimates average effect of the intervention regarding to pre-intervention. Hence, this study help in reducing the output bias using matching algorisms and also help to see the only effect of program intervention among the participant. Though, comprehensive impact assessment research has not yet been conducted to prove it in study area. The central question is whether or not OMFIs have impact on participants' households' poverty reduction? If yes, how much is the impact? Answering these questions empirically would be of interest to program administrators and policy makers in promoting a major change in the preceding approaches. Against this backdrop, this study was carried out in Hosana town of Hadiya Zone, in SNNPRs were different financial institutions have been executing.

1.3. Objective of the study

The general objective of the study is to analyze the impact of microfinance on poverty reduction at household level. Specifically, to examine whether microfinance brought significant differences in living standard of participant compared to non-participant; to assess the impact of omo micro-finance on poverty reduction at household level and to forward policy implication and recommend possible solutions to concerning bodies

2. RESEARCH METHODOLOGY

2.1. Research design

Quasi-experimental research design was used to identify a comparison group that was as similar to treatment group in terms of baseline data (pre-intervention) characteristics. The comparison group captures what would have been the outcomes if the intervention had not been implemented (the counterfactual).

2.2. Participant of the study

The target population estimated in this study was households in Hosana town who are poor and recorded in Wachamo surrounding branch is 2000. The unit of analysis of study was both participants of omo microfinance institution in above branch and non-participants considered as poor and also found in training phase.

2.3. Sampling techniques

A two stage sampling techniques was used in this study to collect primary data from purposively recorded group in institution. Considering the objective of the study and representativeness of the sample, out of the three sub city of Hosana town Sechiduna and Govermeda sub city were selected randomly at first stage. Accordingly, Sechiduna and Govermeda sub city were selected. From sampled sub cities four Kebele were selected randomly two from each. Consequently, the total sample size, 200 household (10 % of targeted household) was randomly drawn from four kebele using simple random sampling procedure via sampling frame (90 household from direct participant and 110 from non-participant of Wachamo surrounding OMFIs loan service.

2.4. Tools of data collection

Source of data to this study were both primary and secondary data. Primary data collected using a structured questionnaire with the help of trained enumerators. The questionnaire includes personal information, socio demographic profile of household head, and outcome variables such as expenditure, income, asset value and saving.

2.5. Data analysis methods

To measure the impact of OMFIs on living standard of household, propensity score matching (PSM) technique was employed. The study attempted to estimate average impact of treatment on treated (ATT)

2.5.1. Estimation of propensity

Estimation of propensity score is the first step in PSM technique and also matching can be performed conditioning only on $P(X)$ rather than on$X$. And then, outcomes without the intervention are independent of participation given$X$ and also independent of participation given $P(X)$ which reduces a multi-dimensional matching problem to a single dimensional problem (Rosenbaum and Rubin, 1983). The logit model was used to estimate propensity score in this study (Caliendo and Kopeinig, 2005). According to Gujarati (2004), in estimating the logit model, the dependent variable was participation, which takes the value of 1 if a household participated in the program and 0 otherwise.

$$P(x) = \frac{e^{zi}}{1+e^{zi}} \quad (1)$$

Where P(x) is probability of participation

$$zi = \alpha 0 + \beta i \sum_{i=1}^{n} \chi i + ui \quad (2)$$

$$1 - p(x) = \frac{1}{1+e^{zi}} \quad (3)$$

$$\frac{p(x)}{1-p(x)} = \frac{1+e^{zi}}{1+e^{-zi}} = e^{zi} \quad (4)$$

$$Li = Ln\left(\frac{p(x)}{1-p(x)}\right) = Ln\left(e^{\alpha 0+\beta i \sum_{i=1}^{n} \chi i + ui}\right) \text{------} (5)$$

2.5.2. **Choice of matching algorithm**

Estimation of the propensity score is not enough to estimate the ATT of interest. This is due to the fact that propensity score is a continuous variable and the probability of observing two units with exactly the same propensity score is in principle zero. From various matching algorithms nearest neighbor (NN), radius and kernel matching methods were applied. However, these methods differ from each other with respect to the way they select the control units that are matched to the treated, and with respect to the weights they attribute to the selected controls when estimating the counterfactual outcome of the treated. All provides consistent estimates of the ATT under the CIA and the overlap condition (Caliendo and Kopeinig, 2005 and Dehejia and Wahba, 2007).

2.5.3. Overlap and common support

Imposing of common support is the third important step in PSM because average treatment effect on treated and on population is only defined in the common support region. As stated by Caliendo and Kopeinig (2005), the common support region is the area within the minimum and maximum propensity scores of treated and comparison groups respectively.

2.5.4. Testing the matching quality

Matching quality has to be checked if the matching procedure is able to balance the distribution of the relevant variables in both the control and treatment group, since conditioning is not on all covariates but on the propensity score. Method of covariate balance used are standard bias, t-test, pseudo-R^2 and joint-significance between participant and non-participants household (Caliendo and Kopeinig, 2005 and Rosenbaum and Rubin, 1985).

2.5.5. Estimating average treatment on treated(ATT)

In a counterfactual framework, the quantity of interest is ATT defined by equation (6)

$$ATT = E(yi1 - yi0) \text{------} (6)$$

A fundamental problem in estimating the casual effect equation (6) is that we will observe only $y_{i1/D=1}$ or $y_{i0/D=0}$. However, the post-intervention outcome is possible to observe but counterfactual ($y_{0i/D=1}$) outcome i.e. the effect of the treatment on the i^{th} household does not participate is not observable in the data and the evaluation problem is characterized by missing data (Rosembaum and Rubin, 1983). Let Yi1 be outcome when the household i is subject to treatment (D=1) and Yi0 the same variable when a household i is exposed to the control (D=0).

$$Yi = DYi1 + (1-D)Yi0;\ D = 0or1 \text{------} (7)$$

Researcher goal is to identify the average effect of treatment on participant and participant households in following manner.

$$ATT = E(Y1i - Y0i/D = 1) = E(Y1i/D = 1) - E(Y0i/D = 1) \text{------} (8)$$

Under conditional independence assumption no-treatment state approximates the no program state Heckman et.al (1998), states that the decision to participate is random conditional on observable covariate X and set of explanatory variable X should contain all the variables that jointly influence the outcome with no-treatment as well as the selection into treatment (Wooldridge, 2002 and Becker and Ichino, 2002). Counterfactual outcome in the treated group is the same as the observed outcome for non-treated group which means that $E(Y0i/D = 1) = E(Y0i/D = 0)$.

$$ATT = E(Y1i - Y0i/Xi, D = 1) = E(Y1i/X, iD = 1) - E(Y0i/xi, D = 1) \text{------} (9)$$

Matching household based on observable covariates might not be desirable or even feasible when the dimensions of the covariates are many. Thus, problem solved by matching along single index variable $p(X)$, which summarizes covariates. It is conditional probability that household i take OMF loan/ well given covariate $P(x) = prob(D = 1/x) = E(D/x)$ (Rosembaum and Rubin, 1983). Equation (8) can be rewritten as:

$$ATT = E(Y1/p(X), D = 1) - E(Y0/P(xi), D = 1) \text{------} (10)$$

The intuition of equation (10) is that two individual households with the same probability of participating were show up in the treated and untreated samples in equal proportions. Through, help of predicted probabilities of participation in the program match pairs are constructed using matching estimators. Finally, impact estimation is the difference between sample mean of outcome variable of interest for program and non-program households for the matched pairs.

$$ATT = \frac{\sum_{j=1}^{p}[Yij1 - \sum_{i=1}^{np}(Yij0)]}{p} \text{------} (11)$$

Where, ATT is total expenditure, asset value and total income and total saving, $Yij1$ is the post intervention outcome variable of household j, $Yij0$ is Pire-intervention outcome variable of i^{th} household of non-program attached to the jth participants, NP is the total number of non-participant and P is the total number of participant household. A positive (negative) value of ATT suggests that households who have participated in OMFIs loan program have higher (lower) outcome variable than non-programs.

2.5.6. Sensitivity analysis

Furthermore, final step in implementation of PSM is checking the sensitivity of the estimated result (Caliendo and Kopeining, 2005). However, a hidden bias arises if there are unobserved variables which affect assignment in to treatment and outcome variable simultaneously which nullify the CIA. This result in biased estimates of ATTs (Rosenbaum, 2002); since matching estimators are not robust against hidden biases, it is important to test the robustness results to departures from the identifying assumption. However, it is impossible to estimate the magnitude of selection bias with non-experimental data. But this problem can be addressed by sensitivity analysis (Caliendo and Kopening, 2005).

3. DATA ANALYSIS AND INTRTPRTATION

3.1. Estimation result

Before proceeding to the estimation process, appropriate diagnostic measures were used on the data and the independent covariate. Results of Multicollinearity test using the values of the variance inflation factor (VIF) shows that there was no serious problem of Multicollinearity. Similarly, the presence of heteroscedasticty problem was tested using Breusch-Pagen test and the existence of heteroscedasticty was rejected with p-value= 0.1849.

3.1.1. Estimation of propensity score

The logistic regression model specified in equation (5) was employed to estimate propensity score for matching treatment household with control household. The dependent variable in this model was binary indicating whether the household were a participant in the OMFI loan which takes a value of 1 and 0 otherwise. The logit estimate result appears to perform well for the intended matching exercise. The pseudo-R2 value 0.2834 shows that the computing households do not have many distinct characteristics overall, so that finding a good match between the treated and non-treated households become easier.

The maximum likelihood estimate of the logistic regression model result shows that program participation status has been significantly influenced by six variables (table3.2) sex of household head, if last 12month there was food shortage in household member, number of dependent in household head, head education level, age of household head and if any credit source other than OMFIs affect probability of participating in microfinance loan program.

Table 3.2: logit regress

Trt	Coef.	Str.Err.	Z-value	p-value
Age	-.0671	.0202	-3.54***	0.000
Lst12mfdshrt	.671	.365	1.84*	0.066
Hhfsize	.3525	.684	.052	0.607
Hhingl12m	.7145	.363	1.97	0.049
Martstus	-.0358	.177	-.20	0.839
Numbdept	-1.175	.703	-1.67*	0.095
Numbwrkforce	.1942	.644	0.30	0.763
Head sex	-6269	.364	-1.72*	0.085
Hheadeduclvl	.5329	.217	2.46**	0.014
Othercreditsource	-1.258	.3762	-3.35***	0.001
Inclvelofhh	.3617	.4143	0.87	0.383
-cons	3.877	1.604	2.42**	0.016

Number of obs=200 LRchi2(11) =78.00 Prob >chi2=0.0000
likelihood = -98.630053 pseudo R2 = 0.2834

*****, **and * means significant at 1%, 5% and 10% level of significance.**

3.1.2. Matching program and non program households

From table3.3below the estimated propensity scores vary between 0.0584247and 0.9739493 (mean=0.625366) for OMFI participant households and between 0.0142306 and .8783146 (mean=0.3065264) for non OMFI participant (control) households. The common support region would therefore, lies between 0.0584247 and 0.8783146 which means households whose estimated propensity scores are less than 0.0584247 and larger than 0.8783146 are not considered for the matching purpose. As a result of this restriction, 24 households (14 participants and 10 non Participants) were discarded.

Table3.3. Distribution of estimated propensity scores:

Group	Observation	Mean	Std. Dev	Min	Max
All household	200	.45	.2817292	.014230	.9739493
Treated group	90	.625366	.2481691	.058424	.9739493
Control group	110	.3065264	.2201286	.014230	.8783146

Source: own estimation result, 2016

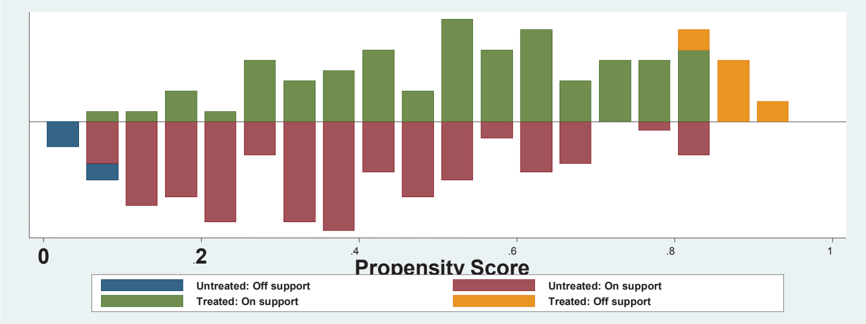

Figure3.2. Kernel density of propensity scores of non participant households

Figure3.2 shows the distribution of estimated propensity scores before and after the imposition of the common support condition for participant and non-participant households, respectively.

3.1.3. Choice of Matching Algorithm

In all matching method, the treated group comprises 76 observations. Whereas, the number of control group comprises 100 observation in all matching methods. Equal mean test, looking in to low pseudo-R^2 value and matching estimator that results in the largest number of matched sample size is preferred were conducted to match the treatment program and control households fall in common support. To sum up, a matching estimator that balances all explanatory variables, with lowest pseudo-R^2 value and produces a large matched sample size is preferable. Table3.4 presents the estimated results of tests of matching quality based on the three performance criteria. Looking into the result of the matching quality, kernel matching of bandwidth (0.25) was found to be the best for the data at hand to researcher. Hence, the estimation results and discussion for this study are the direct outcomes of the kernel matching algorithm with a bandwidth (0.25).

Table3.4. Matching performance of different estimators

Matching estimator	Performance criteria		
	Balancing test*	Psedo-R^2	Matching sample size
Nearest neighbor			
NN(1)	11	0.031	176
NN(2)	11	0.030	176
NN(3)	11	0.033	176
NN(4)	11	0.032	176
Radius matching			
0.1	4	0.284	176
0.25	5	0.284	176
0.5	7	0.284	176
Kernel matching			
Band width 0.1	11	0.035	176
Band width 0.25	11	0.026	176
Band width 0.5	11	0.068	176

*Number of explanatory variables with no significant mean differences between the matched groups.

3.2.4. Testing balance of propensity score and covariate

Once the best performing matching algorithm is chosen, the next task is to check the balancing of propensity score and covariate using different procedures by applying the selected matching algorithm bandwidth (0.25) matching in case of this study. It should be clear that the main intention of estimating propensity score is not to get a precise prediction of selection into treatment. Rather, to balance the distributions of relevant variables in both groups.

Table3.5: propensity score and covariate balance

Variable	Unmatched	Mean		%bias	%reduct	t-test	
	Matched	Treated	Control		Bias	T	p>t
_pscore	U	.62536	.30653	135.9		9.62	0.000
	M	.57088	.53955	13.4	90.2	0.82	0.413
Age	U	52.689	58.836	-67.1	89.4	-4.79	0.000
	M	55.053	55.703	-7.1		-0.48	0.630
Hhfsize	U	4.3111	4.6455	-27.9	48.1	-1.96	0.052
	M	4.3289	4.5025	-14.5		-0.92	0.360
Numbdept	U	2.2222	2.6364	-42.4	64.2	-2.97	0.003
	M	2.2632	2.4115	-15.2		-0.95	0.343
lst12mfdshrt	U	.72222	.48182	50.4	78.2	3.53	0.001
	M	.69737	.7497	-11.0		-0.72	0.474
hhingl12m	U	.62222	.53636	17.4	97.7	1.22	0.224
	M	.60526	.60727	-0.4		-0.03	0.980
Numbwrkforce	U	2.0444	1.9636	10.2	70.6	0.72	0.473
	M	2.0263	2.05	-3.0		-0.18	0.855
Martstus	U	1.5889	1.5455	4.3	56.4	0.30	0.761
	M	1.4868	1.4679	1.9		0.12	0.902
Hhheadsex	U	.43333	.68182	-51.4	93.1	-3.63	0.000
	M	.46053	.47774	-3.6		-0.21	0.833
Hhheadeduclvl	U	1.8111	1.4455	46.0	93.3	3.24	0.001
	M	1.75	1.7254	3.1		0.18	0.861
Inclvelofhh	U	1.1889	1.1455	8.8	74.2	0.62	0.533
	M	1.1842	1.1954	-2.3		-0.14	0.890
Othersorcboring	U	.27778	.53636	-54.3	92.1	-3.80	0.000
	M	.31579	.33619	-4.3		-0.27	0.790

Source: own survey, 2016

To ensure balancing powers: reduction in the mean standardized bias between the matched and unmatched households, equality of means using t-test and chi-square test for joint significance of the variables used are employed. The fifth and sixth columns of Table3.5 above show the standardized bias before and after matching, and the total bias reduction obtained by the matching procedure, respectively. The standardized difference in covariates before matching is in the range of 4.3% and 67.1% in absolute value whereas the remaining standardized difference of covariates for almost all covariates lies between 0.4% and 15.2% after matching and it's fairly below the critical level of 20% suggested. Hence, the process of matching creates a high degree of covariate balance between the treatment and control samples. Similarly, T-values also reveal that all covariates became insignificant after matching while six of them were significant before matching. Low pseudo-R2 value in table 3.2above and the insignificant likelihood ratio tests support the hypothesis that both groups have the same distribution in the covariates after matching. Having this, matching procedure is able to balance characteristics in the treated and the matched comparison groups. Hence, results can be used to assess the impact of OMFI among groups of households having similar observed characteristics.

Table3.6: Chi-square test for the joint significance of variables

Sample	PseudoR^2	LRchi^2	p>chi^2
U	0.261	71.91	0.000
M	0.014	2.92	0.996

Source: psmatch2 result, 2016

All of the above tests suggest that the matching algorithm researcher has chosen is relatively the best for the data at hand. Consequently, researcher proceeds to estimating the average treatment effect on the treated (ATT) for the sample households.

3.1.4. Estimated result of ATT

Using the pre-treatment variables in table 3.5 above propensity score would have been derived using logit regression. With this functional specification the balancing hypotheses are satisfied. Now, researcher offer estimation of average treatment effect on the treated (ATT) of some impact indicator variables. Namely, household's total expenditures, total income, asset value and total saving using the propensity score matching. Based on whether a household's has ever taken loan from OMFI table3.7below provides ATT for total expenditure, asset value total income and total saving estimated via matching of treated and control observations.

Table3.7: Estimation of ATT using propensity score matching

Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
Average annual income	Unmatched ATT ATU ATE	16110.18 16007.67 705.8	701.654 652.742 15575.5	15408.523 15354.928 14869.351 15079.032	698.969 842.236	22 18*
Household annual total expenditure	Unmatched ATT ATU ATE	2800.6 2673.421 2243.01	2256.3 2149.57 2575.25	544.3 523.855 332.238 414.982	156.256 106.951	3.4 4.9**
Home asset Values in birr	Unmatched ATT ATU ATE	3896.68 3757.11 3648.23	3667.59 3764.19 3614.87	229.076 -7.085 -. 33.358 -22.014	299.156 387.802	0.8 -0.02
Total saving	Unmatched ATT ATU ATE	8036.38 8086.70 2980.65	2790.23 3402.52 7266.30	5246.151 4684.037 4285.649 4457.680	912.997 1183.58	5.75 3.9**

Source: own survey data estimation, 2016

In examining impact of intervention in living standard of household, estimated result of table3.7 above

Support the effect of the program on participant households' total income, aggregate expenditure and total saving more likely than non-participant household implying that OMFI loan provision has brought significant impact on programme participants by showing positive ATT value. But in opposing above ideas OMF intervention has not brought impact on investment in household on selected durable asset.

3.1.5. Sensitivity Test

Further, sensitivity analysis was performed on the computed outcome variable to check unobservable biases. At critical level of e^{γ} =1, over which the causal inference of significant microfinance intervention effect must be questioned. The first column of the table 3.8 below shows those outcome variables which bear statistical difference to participants more likely than non-participant household. The result support that effect of microfinance intervention does not change, even though the participant and non-participant households allowed to differ in their odds of being treated up to 220% ($e^{\gamma} = 2.2$) in terms of unobserved covariate.

Table 3.7: Sensitivity test

Outcomes	e^{γ}=1.9	e^{γ}=2	e^{γ}=2.1	e^{γ}=2.2
Total expenditure	0.000019	0.000036	0.000065	0.00011
Total saving	0.000048	0.000089	0.000156	0.00026
Total income	0.004469	0.002396	0.001269	0.000665

Source: survey result, 2016

4. CONCULUTION AND RECOMMANDATION

4.1. Conclusions

This study examined the impact of microfinance on poverty reduction in Hossana town, SNNPR, Ethiopia. The study mainly based on primary data obtained from 200 randomly selected sample households from institution records consisting 90 OMFI program participants and 110 non-participant household using structural questionnaire. In order to estimate the impact of microfinance in poverty reduction PSM is used to create a comparable pair of treatment-control households due to absence of baseline data. Moreover, different processes of matching quality tests were applied such as t-tests, reduction in standardized bias and chi-square tests before calculating ATT. From table3.6 ATT result researcher conclude that participation in Omo MFIs at Hosana town had brought positive and significant impact regarding to total income, total saving, aggregate expenditure of participant household compared to non-participants. Further, sensitivity analysis test on estimated ATT shows that effect of not change even though both group are allowed to differ in their odds of being treated up to 220% ($e^{\gamma} = 2.2$) in terms of unobserved covariates. Hence, ATT result in table3.6 was insensitive to unobservable selection bias, being pure effect of program intervention. Therefore, as far as ATT result was the only effect of intervention, programme intervention reduces poverty at household level.

4.2. Recommendation

The empirical results reported in this thesis led's researcher to forward the following recommendations: The positive impact of Omo MFIs in improving income, aggregate expenditure and total saving implying that OMFI is important in reducing poverty and enhancing social welfare at Hossana town. Therefore, all necessary support should be provided to the industry from the government and other funding organizations in order to improve their performance and outreach as well as to improve the magnitude and type of impacts towards poverty alleviation. Hence, the importance of microfinance in poverty reduction is of immense benefit to the participant households in Hossana town. There is, therefore the need to help sustain it and help its growth as its role to the development of the Hossana town and the country at large is very good.

5. REFERENCE

Asmelash Haile (2003). The Impact of Microfinance in Ethiopia: The case of DECSI in Ganta- Afeshum Woreda of Eastern Tigray. Master Thesis, Addis Ababa University: Addis Ababa, Ethiopia.

Bisrat Gebru (2011). Role of microfinance in alleviating urban poverty in Ethiopia**:** Journal of sustainable development in Africa volume 13, No.6, p168-177

Caliendo, M. and S. Kopening (2005). Some Practical Guidance for the Implementation of Propensity Score Matching: Discussion Paper No. 1588, DIW Berlin and IZA Bonn, and University of Cologne

Deribie Ebisa, Getachew Nigussie, Fikadu Mitiku, 2013**.** Filling the breach of microfinance**:** Journal of Business and Economic Management 1(1): 010-017, Academia Publishing Ethiopia.

Gujarati, D.N., 2004. Essentials of Econometrics: 4th edition. Mc-Graw-Hill Companies. 1003p.

J.J. Heckman, H. Ichimura, and P.E. Todd (1998), Matching as an Econometric Evaluation Estimator. *The Review of Economic Studies*, **65**(2), 261-294.

Mebratu Bayih (2008). Impact of MFI in Urban Poverty Alleviation: Case Study in Addis Ababa, Lideta Sub-City. A Paper Presented for the Association of Ethiopian

OMFIs (2013). Annual report of Hadiya Zone Branch office, OMFIOPM (2013), Hosana, SNNPRS, Hawassa, Ethiopia.

P. R. Rosembaum and D.B. Rubin (1983). Reducing bias in observational studies using sub-classification

P. R. Rosenbaum and D.B., Rubin (1985). Constructing a Control Group Using Multivariate Matched Sampling Incorporating the Propensity Score. *The American Statistician*, 39: 33-38.

Rajeev H. Dehejia & Sadek Wahba (2007). Propensity Score Matching Methods for Non Experimental Causal Studies.

Rosenbaum, Paul R. (2002). Observational Studies. 2nd ed. New York, NY: Springer.

UNDP (2003). Human Development Report: Millennium Development Goals. New York: Oxford University Press.

Wooldridge.J (2002). Econometric Analysis of Cross Section and Panel Data, Cambridge, MA, USA: MIT Press.

Wolday Amah (2001). Experience Sharing Visit of Ethiopian Microfinance Practitioners to Bangladesh. Occasional Paper No.3, AEMFI: Addis Ababa.

….. (2002) Product Development in the Ethiopian Microfinance Industry: Challenges and Prospects. AEMFI, Occasional Paper No .4: Addis Ababa, Ethiopia.

World Bank (2002). Partnership for Development: New York: Washington D.C

…. (2004). Progress in the Fight against Poverty: The World Bank: Washington D.C

World development report (2000/01). Attacking poverty; World Bank: Washington D.C.