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Impact of Micro Finance Institutions on Rural Household Income and Saving; a Case of Illubabur and Bunno Beddells' Ocssco

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Abstract:
Now a day the significance of microfinance in least developing countries especial where the conventional formal bank is lacking is paramount. Microfinance enhances agricultural productivity of the poor farmers those lack access to formal banks due deficiency of collateral. In this paper, we evaluated the impact of microfinance on income and saving of households using cross-sectional household survey data gathered in 2018 from a sample of 304 in South West, Ethiopia. Logit regression and propensity score matching (PSM) techniques were employed for data analysis. The results revealed that adoption of microfinance had a significant positive impact on household income and saving. The results confirm the role of microfinance institutions in improving household income and saving level among microfinance users smallholder farmers is higher compared to non users.Government and microfinance players should work together to make easy the accessibility of the institution to the farmers.

Keywords: Adoption, Income, Saving, Propensity Score Matching, Ethiopia

1. Introduction

Poor households in urban and, in particular, rural areas in many least developing countries do not have access to affordable basic financial services. Their "systematic exclusion" from formal financial services has led to the evolution of an alternative mode of finance, microfinance, in which financial services are provided not through traditional routes, such as local money lenders, cooperatives and banks, but through NGOs or microfinance institutions **(**Asad K. et al,. (2009).

Development paradigm shift was the result of revolution in the Microfinance (MF) industry. The use of MF became an important ingredient for improving the welfare of the poor particularly in developing countries destined by this paradigm shift. This was the result of: (1) the call by The

1997 Microfinance Summit for the mobilization of US$20 billion over a 10-year period to support microfinance; (2) The proclamation of 2005 by the United Nations as the "Year of Micro-credit"; and (3) the ultimate award of a Nobel Peace Prize to a universally acclaimed founder of modern microfinance, Prof. Muhamad Yunus and the Grameen Bank which he founded in 1970. These milestones in the history of MF can be said to have partially boosted the boom in the MF industry. With the start of experimental programs aimed to provide very small credits to groups of poor people, particularly women, to engage in self-employment projects and transform economic and social structures, the model microcredit was invented in Bangladesh (Megersa, 2013).

Today, microfinance is entering an innovative and more dynamic stage. Microfinance sector primarily plays a significant role in the fight against poverty by allowing poor households to raise their income and assets. Microfinance delivers expanded financial services such as deposits, loans, payment services, money transfers and insurance to the poorer and low income segments of the population and their micro-projects (Mamiza H et al, 2008).

By providing financial services to the poor the microfinance institution programs gained a worldwide acceptance and popularity since 1980s. Recent developments in the design of microfinance schemes have come out with innovative features which resulted in reduced costs and risks of making loans to poor and isolated people and made financial services available to people who were previously excluded. Microfinance intervention may increase income, consumption, saving, investment, employment opportunities, better access to nutrition, health care and education.

Ethiopia is one of the poorest countries in the world. Ethiopia's per capita income as estimated by the World Bank is USD 650. Ethiopia is among countries with low HDI (0.448) and ranks 174 out of 188 countries (UNDP, 2016). In 2016, the share of agriculture in Ethiopia's gross domestic product was 37.23 percent, industry contributed approximately 21.31 percent and the services sector contributed about 41.46 percent (IFAD, 2016).

The low profile of Ethiopian economy which is characterized by low growth rate of income, saving, investment, inadequate social services, high population growth and high unemployment rate resembles some of sub Saharan African countries. The country's domestic saving was only

16 per cent of the total GDP (MoFED, 2016). The country faces a huge resource gap to undertake capital formation to accelerate economic growth. To bridge the saving-investment gap, the country has relied on external sources of finance such as loan, aid and foreign direct investment (FDI) in near past. Even by sub-Saharan standards, Ethiopia's domestic saving rate has been very low.

However, favorable macro policy environment and regulatory framework of Ethiopia can encourage sustainable microfinance development (Wolday 2003). The government of Ethiopia supports microfinance institutions as one of the means of addressing the poorest segment of the society to reduce poverty. The government created a conducive environment for the development of microfinance institutions by issuing proclamation No. 40/1996.

The association of small business with microfinance increased income and consumption of beneficiary (Chowdhury & Mukhopadhaya 2012).Poor households are facing a problem of lack of financial resources. The poor are not prone to credit due to ineffective and inaccessibility of formal financial institutions (Assefa et al., 2005). Thus, developing an alternative mechanism for providing financial services to the poor households became critical.

Does access to microfinance really introduce saving habits in rural poor households? There are two conflicting views about this issue i.e. old and new view. The proponents of the old view including Rutherford (2000) and Robinson (2001) argued that poor rural households, particularly in Africa, cannot save because they are too poor. Even if they get some additional income through some windfall, they spend it on consumption or social ceremonies. And therefore, rural saving mobilization efforts are not fruitful and worth nothing.

On the contrary, the new view argued that if rural poor households have access to financial services, they have the capacity and the desire to save and would respond appropriately to saving opportunities and incentives. Among the proponents of this view, Coleman and Williams (2006) argued that the poor do save even though they do not have complete access to savings facilities in formal financial institutions. Empirical evidence shows conflicting finding about the impact of microfinance on the rural poor households saving and income. (Coleman and Williams (2006);Nazrul Islam (2009);Chowdhury&Mukhopadhaya(2012))findings indicates positive impact of microfinance and (Rutherford (2000); Robinson (2001);ADB(2007);Stewart et al.

(2012)) warn the negative impacts of microfinance. Thus this study tries to assess the impact of microfinance on income and savings of rural households of Illu Abba Bori and Bunno Bedelle zones.

2. METHODS

2.1 Selection of study area

Multi stage sampling methods was used to select the respondents. The first stage was selection of 7 woredas from the two zones that is four from Illu Abba Bori and three from Bunno Beddele Zone. The second was selection of Kebeles and the final stage was selection of the household. Data for the study was generated through primary and secondary data. Primary data was collected through a household survey via questionnaire containing a series of questions. Secondary data was gathered from the OCSSC managers via interviews and annual reports were the main secondary data source.

2.2 Selection of households

From each of the selected two zones; 7woredas were selected 4(Darimmu, Bacho, Nopha and Alle) from Illu Abba Bori and 3woredas(Dega, Didessa and Gachi) from BunnoBedelle; since all households in area are socioeconomically, culturally and institutionally similar; sample of household was selected by using systematic random sampling techniques. The household from the selected woredas' which were selected as respondents were categorized in two strata groups; credit users (treated) and non-users (non-treated).The total populations(treated) in the seven woredas are 14917 households and sample size was determined using the following well-known formula (Yamane, 1967).

$$n= \frac{N}{1+N(e^2)} \qquad (1)$$

where: n= sample size

N= number of population e= level of precision(0.05%)

Based on the above formula the total number of sample size were 304.The frist strata (treated) group were 148. Under PSM matching principle number of non- treated group should be greater than that of treated group and the sample size for non treated were 156. Sample was drown from selected Woredas in way of proportionality to their respective population size.

2.3 Methods of Data Analysis

The methods of data analysis used for the study were both descriptive statistics and econometrics models. Descriptive statistics was used to summarize the data on household demographic and socioeconomic characteristics, livelihood assets and similar quantitative data generated by the survey. Econometrics modeling was used to examine the correlate of dependent and independent variables, the impact of credit services on house hold saving and income on credit user (treated). In most studies propensity score matching method has been used to evaluate public policies and programs. This method enable researchers to extract information from the sample of microfinance participants (treated) households and a set of matching households that look like the non-participant (controlled) households in all relevant pre-intervention characteristics. In other words, PSM matches each treated household with a non-participant household that has almost the same likelihood of adopting any social programs. The aim of matching is to find the closest comparison group from a sample of nonparticipants to the sample of microfinance service participants. Thus PSM model was launched to evaluate the impact of microfinance intervention on the credit user's income and saving.

2.4 Model specification

To assess whether the use of credit services is associated with differences in household level income and saving outcomes, the following regression specification may be employed.

$$Y_i = \alpha + \gamma RPT_i + \xi_i \qquad (2)$$

Where Y is a measure of household income and saving; γ is the parameter of interest for estimating the effect of adoption; $\xi$is the model error term . A major methodological challenge associated with the estimation of model (2) through the usual least-square procedure is that the parameter γ would typically be biased–a situation commonly referred to as '*self-selection*' bias (Wooldridge, 2013).This is mainly because households' decisions to adopt the microfinance services is likely not random and that such decisions could be systematically related to other factors that affect household welfare outcomes. Besides, there are also unobservable differences between the two groups of households. The implication is that the two groups are not comparable, and that any difference between the two in terms of welfare (income and saving) cannot be attributed to differences in adoption status alone. Consequently, measurement of impact based on γ fails to separate the effect of adoption (i.e., treatment effect) from that attributable to systematic differences (i.e., selection bias).

To address this challenge, we employ propensity score matching (PSM). The idea of PSM is to construct a comparison group that is based on a model of the probability of participating in the treatment – also known as propensity score (PS) – using observed characteristics and then match participants to non-participants on the basis of this probability. The average treatment effect (ATE) is then calculated as the mean difference in outcomes across these two groups. The validity of PSM depends on two conditions: (i) conditional independence (i.e., the assumption that unobserved factors do not affect participation); and (ii) a sizable common support or overlap in propensity scores across the treatment and control samples. The conditional independence assumption requires that given observable variables, potential outcomes are independent of treatment assignment. This implies that selection into treatment is based entirely on observable covariates, which is a strong assumption. The common support condition, on the other hand, ensures that treatment observations have comparison observations "nearby" in the propensity score distribution (Heckman, LaLonde, and Smith 1999). The effectiveness of PSM also depends on having a large and roughly equal number of treatment and control observations so that a substantial region of common support can be found (Khandker, 2010).

Accordingly, we estimate the ATE of adoption of microfinance services on income and saving level of the households those accessed the services of microfinance. For this, we first estimated the propensity scores, using a logit model specified in equation (1). Only variables that are not possibly influenced by adoption status were included for the estimation. We then matched households using four of the most commonly used matching algorithms: the nearest neighbor (NNM), radius (RM), caliper and kernel (KM) (Caliendo & Kopeinig, 2008).

We then estimated the ATE as the mean weighted difference in outcomes between treated (adopters) and matched control households (non-adopters) using bootstrapped standard errors. To ensure the validity of the common support, we used observations in the common support region only and deleted all other observations whose PS was lower than that of the minimum for adopters and higher than that of the maximum for the non-adopters (Caliendo & Kopeinig, 2008). To determine the best matching algorithm, we employed a performance criteria such as balancing test of covariate means on the matched samples using t-tests. Furthermore, we also tested the balancing properties by re-estimating the propensity score on the matched sample and performing a likelihood ratio (LR) test on the joint significance of all regressors. Accordingly, lower Pseudo R^2 from the re-estimation of the PS and significance of the LR test indicated fulfillment of the balancing properties.

2.5 Treatment variables (participation in microcredit)

It is a dummy variable that takes either 1 or 0 values; 1 for treated group and zero for control groups. Variables like age, distance from market, distance from lending institutions, sex of the household head, education, family size, land size, livestock, off farm participation, marital status, and access to credit were used in PSM for matching purpose.

Outcome variables: the outcome variables included in the study were economic variables (income and saving).

3 Results and Discussion

Under this chapter the data collected with the intent of identifying the impact of microfinance on the income and saving level of the households was analyzed and presented. The discussion has two parts; the descriptive and econometrics.

3.1 Descriptive Analysis

Table 1 below shows summary of the funding of descriptive of household characteristics.

Table 1: Household Characteristics (mean) by access to microfinance status

	Total sample	**Treatment group**	**Control**	**Mean difference**	**t-value(p>t)**
	Mean (STD.dev)	Mean (STD.dev)	Mean (STD.dev)		
Hhage	43.88(8.369)	42.467(9.011)	44.38 (8.099)	1.912	1.55(0.121)
Farmlabor	3(1.06)	2.95(1)	3.09(1.1)	0.141	1.1(0.24)
Livestock	6.79(1.96)	6.66(1.93)	6.89(1.95)	0.23	1.04(0.298)
Inputs	1826(1146)	2125(1000)	1567(1202)	557.66	4.35(0.000)***
Dishom	3.87(1.67)	1.67(1.1)	5.76(2.5)	4.08	17.46(0.000)***
Dismark	5.33(2.1)	4.79(1.55)	5.8(2.38)	1.21	4.29(0.000)***

Source: from data (2018)

As depicted on the above table there is significant difference between the mean values of the amount of money spent for input for the two groups. Microfinance users spent more on purchase of improved agricultural inputs which improve the production and income of the users. The finding in the study area was in line of the arguments of the positive contribution of microfinance expansion in promoting the agricultural productivities of the farmers.

Distance of the microfinance institution from the user's house is another variable which determine the farmers to use the services of the microfinance. There is significant distance difference among the two groups. On average the user house is 1.6 km far from the microfinance institution and that of non user located on average at the distance of 5.7 kms from the institutions. This indicates that distance of the microfinance institution from the farmer's house is the major variable which affects the likelihood of the farmers to use microfinance institutions services which in turn affect the livelihood of them.

As indicated on the above table 1 there is significant mean difference between the two groups distance of the market from the home of the farmers. Microfinance users are located on average at the distance of 4.7 km.

Table 2: Summary of discrete variables values.

Variables		Credit users	Non user	Pearson Chin square
		%	%	
Sex of the house head	Male	88.71	96.59	5.51(0.019)
	Female	11.29	3.41	
House head education	Literate	67.74	42.61	11.58(0.001)
	Illiterate	32.26	57.39	
Access to irrigation	User	25.81	41.48	4.80(0.028)
	Non users	74.19	58.52	
Access to information	Accessed	66.13	56.82	1.64(0.199)
	Not accessed	33.13	43.18	
Extension	Accessed	56.45	78.98	11.83(0.001)
	Not accessed	43.55	21.02	

Source: own computations from data (2018)

The average value of the categorical variables of the two groups (microfinance service user and non user) are indicated on the above table. The result indicates that there is significant difference on sex of household heads. 88.71% of the users are male and the remaining 11.29% of them are female. This indices that male participate in microfinance service is on better position than that of their counterpart.

The role of education in improving life style and livelihood of human is irreplaceable by another factor. The data indicates that majority of the users are literate. There is significant difference between the two groups on their education status. Users are more educated than non users.

Irrigation effects the decisions of the household in many aspects. According to the data collected there is significant difference between microfinance users and non users on the use of irrigation. 25.81% of credit users use irrigation while the remaining 74.19% did not participate on irrigation. On the other side there is no significant difference between the two groups on access to information and extension services.

3.2 Propensity Score Analysis for Identifying the Impact of the Program

The logit model is the prominent model used under propensity score to identify whether there are significant difference between credit users and non users on the observed variables. The results of propensity score of program participant and non participant is used to identify the common support region.

Table 3: Estimates results of the binary logit model

Accredit	Coefficient	Std. Err	Z	P>	[95% confidence interval]	
Sexhead	-.3860787	.3641493	-1.06	0.289	-3.11347	-.2668572
Hhage	.0256019	.0146149	1.75	0.080	-.0559426	.0574144
Hheduc	.6702557	.1990459	3.37	0.001	.280133	1.060378
Famlabor	.3706494	.1268345	2.92	0.003	.1220584	.6192404
Acinfo	.1010236	.1929657	0.52	0.601	-.2771823	.4792295
Livestock	-.1432568	.0501312	-2.86	0.004	-.2415122	-.0450014
Input	.0002323	.0001124	2.07	0.039	.0000121	.0004526
Dishom	-.3790855	.1953529	-1.94	0.052	-.7619701	.0037991
Dismrkt	-.0696098	.0575981	-1.21	0.227	-.1825	.0432805
Acexten	-.4671322	.192937	-2.42	0.015	-.8452817	-.0889827
Acirrig	-.7040234	.7571946	-0.93	0.352	-2.188098	.7800507
Cons	-.7040234	.7571946	-0.93	0.352	-2.188098	.7800507

Logistic regression Number of observation= 304

LR ch2(11)=65.50

Prob>chi2=0.0000

Log likelihood= -177.860 Pseudo R^2=0.1555

Source: Computed from own survey data (2018)

The logit estimate of the model indicates that out of eleven variables five (age of household, input, education status, extension services, farm labor and livestock ownership) of them are significant and the remaining six(access to irrigation, distance from the market and microfinance center, modern input use, access to information and age of the household) are insignificant .

As can be seen from the summary statistics of propensity scores in Table 4 the predicted propensity scores for microfinance users and non-users ranged from .1328524 to .8974477. The common support region was satisfied in this range after discarding 12 observations from microfinance users group.

Table 4: Predicted Propensity Score in the Common Support Region
Source: Own Survey data (2018)

The choice of matching algorithm was carried out based on three criteria; namely, balancing test, Pseudo R-square and matched sample size. The estimator that balances more independent variables, low pseudo R-square value and results in large matched sample was then chosen as being the best estimator. Accordingly, kernel matching method [i.e., kernel(0.1)] was found to be the best estimator, since it resulted in the least pseudo R-square (0.008), had insignificant LR chi-square (LR = 2.93, p = 0.997) (Table 5).

Table 5: Matching Algorithms Analysis Before and After Match

Observations	**Mean**	**Std.Dev**	**Min**	**Max**
Microfinance non user	.391535	.1829218	.0765975	.8974477
User	.5882638	.2143523	.1328524	.9940768
Total	.4873108	.2216045	.0765975	.9940768

Source: own computation (2018)

Matching Algorithm	Before matching				After matching		
		Pseudo R2	LR Chi2	P-value	Pseudo R2	LR Chi2	P-value
NN	(1)	0.1555	65.50	0.000	0.015	5.60	0.935
	(2)	0.1555	65.50	0.000	0.017	6.27	0.902
	(3)	0.1555	65.50	0.000	0.015	5.72	0.929
	(4)	0.1555	65.50	0.000	0.015	5.55	0.937
	(5)	0.1555	65.50	0.000	0.013	4.82	0.964
KM	(0.1)	0.1555	65.50	0.000	0.008	2.93	0.996
	(0.25)	0.1555	65.50	0.000	0.011	4.30	0.977
	(0.5)	0.1555	65.50	0.000	0.059	22.33	0.034
RM	(0.01)	0.1555	65.50	0.000	0.123	32.30	0.001
	(0.1)	0.1555	65.50	0.000	0.123	32.30	0.001
	(0.25)	0.1555	65.50	0.000	0.114	32.30	0.001
Caliper	(0.1)	0.1555	65.50	0.000	0.015	5.60	.935
	(0.25)	0.1555	**65.50**	**0.000**	**0.015**	**5.60**	**0.935**
	(0.50)	0.1555	65.50	0.000	**0.015**	**5.60**	0.935

A glance at Table 5 shows that the main estimated treatment effects from the propensity score matching. We find that microfinance services use had significant effect on household income as evidenced by the significantly higher income resulting from access to credit ($p<0.01$).

Table 6: The Average Treatment Effect on the Treated

Outcome	Treated	Controls	Difference	T-stat
Income	20188.62275	16564.73	3623.89275	3.78***
Saving	6317.82353	4064.72998	2253.09355	3.46***

Source: own computation (2018)

As indicated on the above table microfinance users are on better position when compared with non user in terms of income and saving. Households those adopt microfinance get 3623.89 more annual income than those controlled groups and also adopters save 2253.09 income compared to non users. Thus in the study area the use of microfinance services play positive impact on improving the livelihoods of the farmers.

Conclusion

Microfinance use results in substantially increased household income and saving. A propensity score matching approach was used to compare microfinance services user's households with non-users in terms of two key measures of household well being; income and saving measured by Ethiopia Birr. The matching techniques employed were the nearest neighborhoods matching, radius matching, caliper matching, and kernel matching. Among the algorithms used kernel matching (0.1) was found to be the best estimator of data based on balancing test, pseudo R^2 and sample size. The results showed that access to microfinance had significantly positive impact on farmers' income and saving. In addition to that, factors such as; the sex of households, education level households, farm labor, holding of livestock, and extension services access were found to be important variables to affect farmers' tendency to use microfinance services.

The implication of the findings is straightforward; even if the adoption of microfinance services is quite low in the study area, those households who could use the services of microfinance could generally improve their income and saving. Therefore, it is mandatory to scaling up the accessibility of microfinance institutions as one option to enhance farm yields, household income and saving, and household agricultural input expenditure in the study area while introducing new agricultural practices and technologies is another option.

The following core points are presented as recommendations in order to improve the adoption level and income gained from microfinance adoption technology in the process of wheat grain production.

- Expansion of microfinance services adoption involves the use of different practices, which require knowledge, and skill of application and management. Education was found to have a strong relation with the adoption of microfinance in the study area as it enhances household saving and income. Therefore, due emphasis has to be given towards strengthening rural farmers' education at different levels for small farm households.

- The distance of the microfinance institutions from the home of the households is among the factors which affect the adoption of microfinance services. Thus these institutions should open their office as close as possible to the kebele level. Up to now the institutions restrict their office to the woreda level. Thus to increase their clients at least they have to establish their office at cluster level.
- The role development agents (DA) in transforming rural households is paramount. In the study areas access to extension services positively affect the decision of the farmers to use microfinance. Thus strong follow ups should be undertaken by the concerned body to improve accessibility of the rural community to information.

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