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Determinants Of Farm Households' Participation in Microfinance Program and Its Impact on Their Livelihoods: The Case of Boneya Boshe Woreda of East Wollega Zone, Oromia, Ethiopia

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Abstract

Microfinance is an institution that provides access to various financial services such as credit, savings, leasing to low-income clients. Therefore, the objective of this study was to identify factors that affect farm households' participation in microfinance programs and its impact on their livelihoods). In order to achieve these objectives, both primary and secondary data were collected. Primary data was collected using semi-structured questionnaire and interview. While secondary data was collected from different published and unpublished documents. Multi-stage stratified sampling technique and systematic random sampling technique were followed to reach 364 sample respondents out of 4,045 total farm households of the selected kebeles. Descriptive, inferential, and econometric methods were used to analyze the data. Binary Logit regression model and Propensity Score matching technique were applied by using stata software version 15. Logistic regression result indicates that program participation was significantly and positively affected by family size, education level, farm size, risk perception, extension visit and training access of household head whereas distance of household home from microfinance office has negative effect. The result of sensitivity test using Rosenblum bounds also implies that the estimated impact result was insensitive to unobserved characteristics. Furthermore, PSM result indicates that microfinance program has a significant and positive impact on income of participant households. Finally, the study recommends that microfinance institutions and other concerned stakeholders should broaden their outreach and expand their access to rural areas in enhancement of rural farm households' livelihoods.

Keywords: Binary Logit regression, Farm Households', Livelihoods, Microfinance Program, Propensity Score Matching, Ethiopia

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1. Introduction

Microfinance has become a common term in the development of vocabulary since its introduction in the 1970s. Although the word is literally composed of two words; micro and finance which literally mean small credit; the concept of microfinance goes beyond the provision of small credit to the poor (Bernard et al., 2017). According Abdul et al. (2018), microfinance is the provision of a variety of financial service such as small size of loans, saving, insurance services, money transfer and other relevant services to the target poor people who were not served by conventional banks due to lack of collateral requirements.

Amsalu (2019) also defined the term microfinance institutions as the provision of small sized financial service to the poor who were in need of financial services but lack access to formal commercial banks. Moreover, microfinance is an economic development approach that involves providing different financial services through institutions to low income and poor peoples. The services provided by the microfinance institutions (MFIs) include credit, savings, payment service, insurance services, and other services. The loan characteristics include, small amount of loan, short-term credit (a year or less), no collateral requirement, poor borrower and mostly women who are not qualified for a conventional bank loan. The loan pays high interest rates because of the high cost in running microcredit program (Ayen, 2016).

Across the globe, microfinance has been considered as a solution to alleviate poverty and ease the hardship of livelihood of many poor people (Mengistu, 2017). It is taken as a strategy to overcome the constraints of conventional bank in reaching the poor and seen as one of the most efficient instruments to promote economic development, livelihood improvement and diversification and in fighting against poverty in poor countries (Chirkos, 2014). Similarly, in Africa and other developing countries, it is often viewed as a means of lifting people out of the vicious circle of poverty (Lemesa, 2019).

Access to credit through microfinance can help rural poor economy by increasing the ability of households to meet their financial needs such as the purchase and use of improved agricultural inputs which are not available from the farm. Moreover, access to rural credit may increase the households' ability to adopt modern agricultural technologies that increase their income and breaks poverty cycle (Wossen et al., 2017). It enhance household livelihood by increasing their income and smoothing consumption through a variety of ways including income generating sources, self-employment, and an increase of savings and minimizing risk of vulnerability (Mengistu, 2017).

Furthermore, the task of microfinance is crucial in the course of improving low-income and poor people's livelihoods. It allows poor people to diversify their sources of income, and it is the essential pathway to depart from poverty and hunger. Access to microfinance service enables the low-income people to smooth their consumption, manage their risks better, build their assets gradually, and enhance their income producing capacity. Thus, microfinance helps to promote an improvement in life of household (Rehman et al., 2020).

In Ethiopia also, many microfinance institutions have been established and working in order to solve the credit access problem of the poor. They are established by proclamation no. 40/1996 and this gives them the legal frame for their establishment. Since the issuance of this proclamation in July 1996, thirty-five microfinance institutions have been legally registered and delivering microfinance service in the country. Among these microfinance, Oromia credit and saving share company is one of the largest microfinance institutions established in accordance with the above mentioned proclamation in 1997 (AEMFI, 2017).

Following the directive of the National Bank of Ethiopia (NBE), \ microfinance institutions to evolve into commercial banks with a two-year transition period executives of the microfinance made the transformation from microfinance to banking service with not discounting the microfinance operation. Oromia Credit and Saving Share Company (OCSSCO) is currently relicensed to provide banking service in consort with its long existing microfinance wing based on the proclamation No. 626/2009 and National Bank of Ethiopia directive No. SBB/74/2020. The company has also been renamed to Sinqe Bank called after the cultural institution of Oromo women.

The prevailing operations of conventional financial institutions in many developing countries such as Ethiopia are inefficient in providing sustainable credit facilities to the poor. The formal financial institution like bank and insurance that could provide credit service for low income like hand crafts, pastoral and farmer's families are very limited in Ethiopia and most of the poor access financial service through informal channels such as *Iqub, mahiber*, money lender, relatives, friend and etc (Lemesa, 2019).

The major reasons formal financial institutions financially exclude the low-income people are associated with high risks and costs. There is an enormous amount of uncertainty with regard to the repayment ability of the poor. Information about credit is inadequate or unavailable, and the majority of the poor do not have collateral. Hence, it became necessary for the government to start promoting other initiatives to ease access and use of financial services. As a result, many microfinance schemes have been established to provide financial service to the poor people living in urban and rural areas of the world (Duvendack et al., 2011).

Since its establishment in the 1970s, microfinance has captured the attention of researchers throughout the world and empirically different impact assessments were undertaken to show whether the program has brought in promoting households livelihood or not (Aregawi et al., 2019). However, the available knowledge concerning the achievements of these studies is still inconclusive. There is controversial argument among the researchers with regard to the impact of microfinance programs on the livelihoods of clients. Some empirical findings indicate that microfinance programs have a positive impact on client livelihoods while others argue that microfinance has a negative impact on clients' household livelihoods.

Specifically, in Ethiopia also, there are studies that examined the impact of microfinance on the livelihood of its users and get different findings. For instance, Bekele & Getachew (2014), Challa & Mansingh (2015), Ayen (2016), Alemu (2018), Geleta et al. (2018), Lemesa (2019), provide positive evidence for the positive impact of microfinance intervention. However, some studies revealed that the impacts of microfinance institutions on clients' income were minimal (Desai et al., 2011; Siyoum et al., 2012; Tarozzi et al., 2013).

Thus, to the best of the researcher knowledge, there is no consensus among scholars and researchers on the impact of microfinance on client's income and most of the research in this area is descriptive with few statistical tests. Additionally, the researcher could not find any study undertaken on the determinant of farm households' participation in microfinance program and its impact on their income in the study area. Therefore, this study was designed to identify the factors which affect farm households' participation in microfinance programs and to evaluate the impact of microfinance programs on the income of farm households' in Boneya Boshe woreda by using more descriptive statistics and econometric model through logit and Propensity score matching model.

The general objective of the study was to identify the major determinants of participation farm households in microfinance program and its impact on their income in the case of Boneya Boshe Woreda of East Wollega Zone, Oromia, Ethiopia. While specific objectives of the study were to examine the major reasons for borrowing by the farm households' in Boneya Boshe woreda, to investigate the factors that affect participation of farm households in microfinance program in the study area and to analyze the impact of participation in microfinance program on farm households' income in Boneya Boshe Woreda.

2. Research Methodology

2.1. Description of the Study Area

Boneya Boshe woreda is one of the 17 woredas in East Wollega Zone of Oromia region and it was part of former Wama Boneya woreda. Billo is the administrative center of the district located 301 KM to the West of the capital city Addis Ababa and 81 KM to the East of the zone capital, Nekemte. Geographically the Woreda is situated at the longitude 913N- 927N and latitude of 36044E-37009E. The altitude range of the Woreda is between 1551 to 2718 meters above sea level. The Woreda is bordered in the North by Sibu Sire and Gobu Seyo Woreda of East Wollega Zone, on the South by Nono Benja Woreda of Jimma Zone, on the East by Bako Tibe and Ilu Galan Woredas of West Shewa Zone and on the West by Wama Hagalo Woreda of East Wollega Zone with a total land area of 47,439,888km^2. Administratively, the woreda is divided into 12 kebele administrations; 10 rural and 2 urban kebele administrations (Administration office of Boneya Boshe woreda, 2022).

The woreda has two conventional banks (one government bank and one private bank). Namely, Commercial Bank of Ethiopia and Cooperative Bank of Oromia and a single microfinance institution is providing a microfinance program in the woreda which is popularly known as OCSSCO and recently changed to Sinqe Bank (Administration office of Boneya Boshe woreda, 2022).

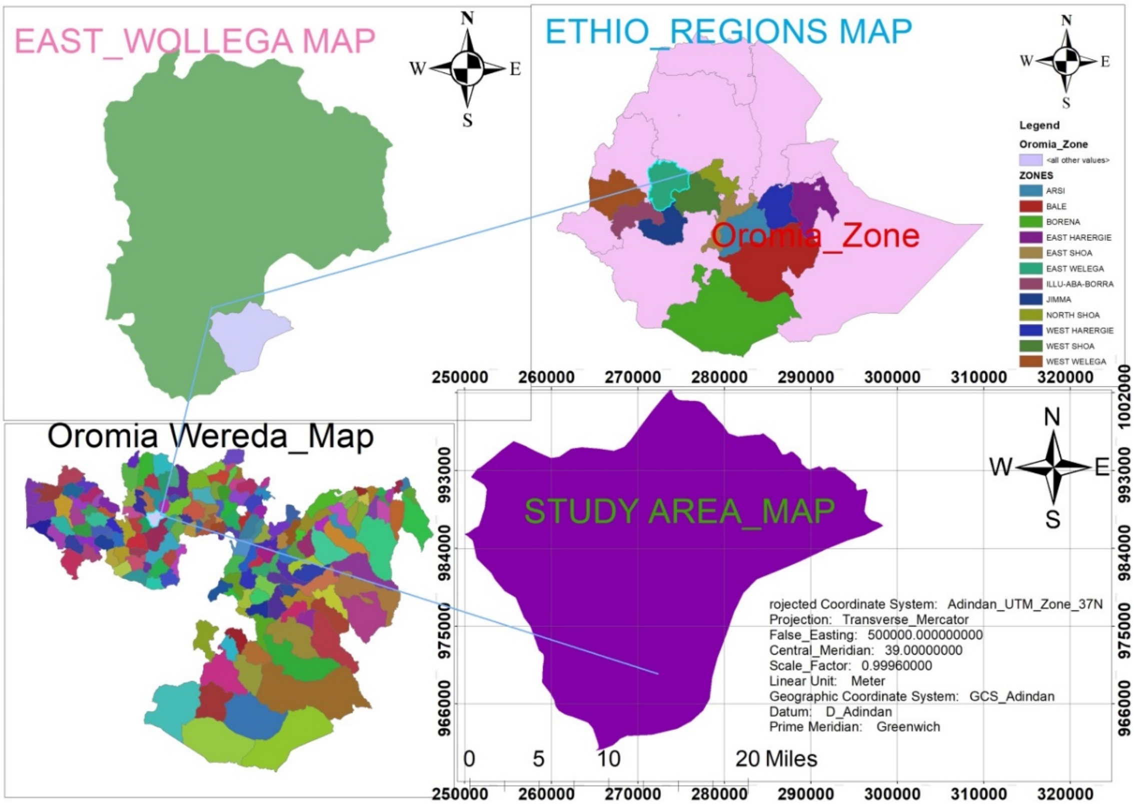

Figure 2: Location map of the Study area

Source: Administration office of Boneya Boshe woreda (2022).

2.2. Research Design

In order to conduct research on the study area, data was collected once from a sample selected to describe the larger population at that time. Thus, the researcher adopted a cross-sectional survey. The population was a constitute of farm households' participants and non-participants of microfinance program, in this case Boneya Boshe woreda of East Wollega zone and unit analysis was farm households. For sampling techniques, multi-stage sampling technique was used to select representative samples for the study. Data was analyzed using descriptive statistics and econometric model through logit and PSM.

2.3. Data Source and Collection Methods

The study used primary and cross-sectional type data. This design was adopted because there is no baseline data available that could serve to employ time-series or longitudinal design. Primary sources were collected through questionnaires from selected farm households on a variety of respondent demographic characteristics, socio-economic variables and institutional factors. The questionnaire was designed in such a way to capture the necessary information on household level livelihood indicators based on the objective of the study.

The study also supplemented data from secondary sources. Secondary data were obtained from published and unpublished documents, obtained from microfinance institution in Boneya Boshe woreda, Boneya Boshe administrative office, relevant literature and other relevant organizations. After this, quantitative and qualitative data were collected and analyzed to respond to questions that were raised in the study area.

2.4. Sampling Technique

Multi-stage sampling technique was used to reach the selection of a sample of rural farm household's participants and non-participants of microfinance in the study area. In the first stage, out of the total 17 woreda of East Wollega zone, Boneya Boshe woreda was purposively selected due to the existence of single MFIs in Boneya Boshe woreda, which has more duration of time in the program.

The sample size was determined based on the formula given by Yamane (1967). Yamane provides a simplified formula to calculate sample size. This formula was used to calculate the sample size from a given population at 95% confidence level and 5% precision level. Accordingly, sample size was estimated as follows:

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

Where n=sample size, N=population size, and e= the level of precision.

The total number of farm households in the selected kebeles is 4,045. Therefore, sample size can be obtained by using the above formula.

$$n = \frac{4{,}045}{1+4{,}045(0.05)^2} = 364$$

After determining the total sample size of the selected kebeles, then the stratified sample size of each selected kebeles was determined proportionately as follows:

$$n_i = \frac{N_i}{N}(n)$$

Where n_i = the total number of selected samples from each i^{th} selected kebeles.

N_i= the total number of farm households' from i^{th} selected kebeles

N= the total number of farm households in the selected kebeles.

n= the total sample size

Accordingly, the sample size for each kebeles is calculated as follows:

Yada Hunda $(n_1) = \frac{N_1}{N}(n) = \frac{1{,}422}{4{,}045}(364) = 128$

Gala Gure $(n_2) = \frac{N_3}{N}(n) = \frac{1{,}224}{4{,}045}(364) = 110$

Jawis $(n_3) = \frac{N_2}{N}(n) = \frac{855}{4{,}045}(364) = 77$

Qare Konchi $(n_4) = \frac{N_4}{N}$ (n) $= \frac{544}{4{,}045}(364) = 49$

Therefore, the total number of farm households' sample size of the selected kebeles is the sum of farm households' sample size of each selected kebeles.

n = $n_1 + n_2 + n_3 + n_4$ = 128+110 +77+49 = 364

The study used both descriptive and econometric methods of data analysis. The descriptive analysis was applied to examine demographic characteristics, institutional factors and socio-economic profiles of the household and performed using descriptive indicators such as frequency, mean, and percentages. While the econometric analysis was applied to identify the variables that affect farm households' participation in microfinance program and to evaluate its impact on their income.

2.5. Model Specification

The Binary Logistic Regression Model

Binary logistic regression was adopted to analyze the relationships between a dichotomous dependent variable and explanatory variables. Logistic regression combines the explanatory variables to estimate the probability that a particular event will occur, that is a subject will be a member of one of the groups explained by the dichotomous dependent variable.

Where the dependent variable is dichotomous, Probit and Logit models are appropriate. The probit probability model is associated with normal probability function and the logit model with logistic probability distribution respectively. Both logistic and probit models may give the same result. Though both logistic and probit give the same result, the logistic model is selected for this study. The rationale for using logistic model than probit model is, it represents a close approximation to the cumulative normal distribution, mathematically easily used and is easier to work with. Moreover, the justification for using logit model is its simplicity of calculation and its probability lies between 0 and 1 and its probability approaches to 0 at a slower rate as the value of independent variable gets smaller and smaller, and the probability approaches 1 at a slower rate as the value of the independent variable gets larger and larger (Gujarati, 2003).

In order to examine the probability of farm households' participation in microfinance program, logit model was selected for this study. The model was fitted using participation in microfinance program as dependent variable and socioeconomic, demographic variables and institutional factors (Gender, age, marital status, educational level, family size, distance of household home from microfinance institutions, access to training, cultivated farm size, *equb* member, extension visit, livestock size, and household perception to risk) as independent variables which simultaneously influence farm households' participation in microfinance program and the outcome variable. The dependent variable is binary, taking values of "1" if farm households' participated in microfinance program and "0" otherwise. However, the independent variables are both continuous and discrete.

The mathematical formulation of the logit model is shown below.

$$\text{Pi} = \frac{e^{Zi}}{1+e^{Zi}} = \frac{1}{1+e^{-Zi}} \quad (1)$$

Where Pi= the probability of participation in microfinance program forthei^{th}farm households'

The probability that a farm household belongs to non-participant in microfinance program is.

$$\text{1-Pi} = 1 - \frac{1}{1+e^{Zi}} = \frac{1}{1+e^{Zi}} \quad (2)$$

The ratio of the probability that a farm household's is participant in microfinance programs to the probability of non-participant farm households in microfinance is the odds ratio.

Therefore, the odds ratio can be written as.

$$\frac{Pi}{1-Pi} = \frac{1/_{1+e^{-zi}}}{1/_{1+e^{zi}}} = \frac{1+e^{Zi}}{1+e^{Zi}} = e^{Zi} \quad (3)$$

Finally, taking the natural logarithm of the Equation 3 (odds ratio) can be written as follows:

$$\text{Ln}\left[\frac{P_i}{1-P_i}\right] = \ln e^{Zi} = \text{Zi} = \beta_0 + \beta_1 X_i + \beta_2 X_i + \dots\dots\dots\dots\dots. + \beta_n X_n \quad (4)$$

Equation (4) with disturbance term can be written.

$$\text{Zi} = \beta_0 + \sum_{i=1}^{n}(\beta_i X_i) + U_i \quad (5)$$

Where Zi = function of explanatory variables (Xi)

β_0= intercept, β_1,β_2 ……… β_n are the slopes of the equation in the model

X_i = independent variables and U_i = disturbance term.

Pi=βo+β1(GENDER)+β2AGE+β3(MARST)+β4(FAMSIZE)+β5(EDUC)+ β6(FARMSIZE)+β7(LSTOCK)+β8(RISKPERC)+β9(DISTANCE)+β10(TRAIN) + β11(EQUB)+β12(EXTVST)+ Ui

Where, Pi = the probability of participation in microfinance program for the i^{th} farm households'

Propensity Score Matching (PSM) Model

In this study, PSM model was employed to see the impact of microfinance on outcome variable (income). The reason for the adoption of these models is, the study lacks baseline data or longitudinal data and thus depends on cross-sectional data for which PSM model is more appropriate.

The PSM technique enables us to extract information from the sample of treated/participant farm households' and a set of matching /non-participant farm households'/control group that look like the participant/treated farm households in all relevant pre-intervention characteristics. The objective of PSM is to find the closest comparison group from a sample of non-participant farm households' and participant farm households. Closest will be measured in terms of observable characteristics. Farm households' with the same propensity scores was paired and the average treatment effect on the treated (ATT) was then be estimated by the difference in outcome between the treated and control/comparison group (Greene, 2012).

In this study, the main pillar of Propensity score matching (PSM) is participation in microfinance, farm households' participants in microfinance program, and potential outcome variable (income). The idea was to match farm households' that participates in microfinance with that of non-participants in microfinance program sharing full observable characteristics. Then the average effect of participation in microfinance program was measured as the average difference in income between the participants/treated group and non-participants /control group in microfinance program.

The use of propensity score matching model is to answer the question "what the income of farm would be households' who participated in microfinance program had these rural farm households' not participated in microfinance?" Participants (treated) and non-participants (control group) of farm households in microfinance program are related on some characteristics (Gender, age, educational level, family size, distance of household home from microfinance institutions, cultivated farm size, *equb* member, extension visit and livestock ownership). These variables are important to identify comparison groups.

According to Rosenbaum & Rubin (1983), PSM can be explained as the conditional probability of taking a treatment given pre-treatment characteristics. The propensity score model is defined as:

$$P(X) = \Pr(D=1|X_i) = E(D|X_i) \quad (6)$$

Let, Y_i^T −is outcome of treated (income) in birr of i^{th}farm households', when he/she is treated, Y_i^C:is outcome of control (income) in birr of i^{th}farm households', when he/she is controlled and ΔI: change in outcome between the treated and control group. Therefore, the difference in outcome between the treated and control group can be calculated from the following mathematical equation:

$$\Delta I = Y_i^T - Y_i^C \quad (7)$$

Let the above equation be determined in causal effect notational form and in this study 'D' represent participation in microfinance which is a dummy variable such that D=1 if farm households' is participant in microfinance program and D=0 otherwise. Then, the formula for average treatment effect on the treated (ATT) can be seen as follows:

$$ATT=E(Y_i^T\text{-}Y_i^C|D_i = 1) = E\ (Y_i^T|D_i = 1) - E\ (Y_i^C|D_i=1) \quad (8)$$

Where E $(Y_i^T|D_i = 1)$ =Average outcome for participant farm households' if they participated in microfinance program

E $(Y_i^C|D_i = 1)$ =Average outcome for participant farm households' if they were not participated

ATT=Average treatment effect on the treatment for the sample.

$$ATT= E\ (Y_i^T - Y_i^C|D_i = 1) =E\ (Y_i^T|D_i = 1) - E(Y_i^C|D_i = 1) \quad (9)$$

The main problem in the evaluation of impact is, it is difficult to observe a person's outcome for with and without treatment at the same time. The post-intervention outcome $(Y_i^T|D_i = 1)$ can be observable, however, the counterfactual outcome of the i^{th}farm households' when he/she does not treat, the treatment is not observable in the data. Therefore, an alternative counterfactual has to be constructed through the formation of control groups that resemble the observed outcomes of participants or the treatment group. The ATT was used to estimate the true impact as follow as;

$$ATT =E\ (Y_i^T - Y_i^C|D_i = 1) = E\ (Y_i^T|D_i = 1) - E(Y_i^C|D_i = 0) \quad (10)$$

There are two important assumptions that need to be satisfied for the PSM model to correctly estimate the impact of participation in microfinance on outcome variable (income). These are the Conditional Independence Assumption and the Common Support Condition.

Conditional Independence Assumption (CIA): It indicates that outcomes are independent of treatment and conditional on (Xi). This assumption shows that the selection is only depend on observable variables that affect participation decision of households and outcome variables simultaneously (Caliendo & Kopeinig, 2008).

$$(Y_i^T, Y_i^C) \perp D|X \quad (11)$$

Common Support or Overlap assumption: A further assumption besides conditional independence (CIA) is the common support or overlap condition. The assumption is that P(x) (probabilities) lies between 0 and 1. This restriction implies that the balancing property is performed only on the observations whose propensity score falls in the common support region of treated and control groups (Becker & Ichino, 2010). Individuals that lie outside the common support region would be discarded in the estimation of treatment effect. That is;

$$0 < P\ (D=1)\ |X<1 \tag{12}$$

Matching Algorithm

There are a number of matching estimators, which can be employed. The most common matching algorithms used in PSM are nearest neighbor matching (NNM), caliper matching (CM) or radius matching (RM), Stratification or Interval matching, and kernel matching (KM) were used to evaluate the impact of microfinance on income of farm households'.

Nearest Neighbor matching: Nearest neighbor is the straightforward matching estimator. In a nearest neighbor matching, farm households from the comparison group is chosen as a match for a treated farm households' in terms of the closest propensity score or similarity in terms of observed characteristics. Farm households from the controlled group are chosen as a matching partner for a treated farm household that is closest in terms of propensity scores. For each treated farm household's i, a control farm household's j that has the closet scores in terms of the observable characteristics was selected. A propensity score that minimizes the distance between the treated and untreated defines the nearest neighbor matching algorism.

Caliper or Radius matching: NN matching faces the risk of bad matches, if the closest neighbor is far away. This can be avoided by imposing a tolerance level on the maximum propensity score distance (caliper). To overcome this problem the caliper-matching algorithm is another alternative. Radius matching means that an individual from the comparison group is chosen as a matching partner for a treated individual that lies within a given caliper (propensity score range) and is closest in terms of propensity score (Caliendo & Kopeinig, 2008). Imposing a caliper works in the same direction as allowing for replacement. Bad matches were avoided and hence the matching quality rises. However, if fewer matches can be performed, the variance of the estimates increases.

Stratification or Interval matching*:* Interval matching calculates the programs effect by using intervals. Interval is a time or space between two periods or objects. Within each interval, the program effect is counted by the mean difference in outcomes between treated and control observations. To each interval, average weights are assigned and share of each participant is measured according to given weights.

Kernel matching: Kernel matching are non-parametric matching estimators that compare the outcome of each treated farm households' to a weighted average of the outcomes of all the untreated farm households' with the highest weight placed on those with scores close to the treated rural farm households'. Caliendo & Kopeinig (2008) argue that Kernel matching uses weighted average of all rural farmers in a comparison group to construct the counterfactual outcome. The assignment of weights depends on the distance between each rural farmer from the comparison group and treated rural farmers for which the counterfactual is estimated. Therefore, more weight was assigned to comparison rural farm households 'whose propensity score is closer to that of the treated group. Each rural farmer from the treated group was matched with several control rural farmers with weights inversely proportional to the distance between treated and control group.

Testing the Matching Quality

Since we do not depend on all covariates but on the propensity score, it has to be checked if the matching procedure is able to balance the distribution of the relevant variables in both the comparison and treated group. The purpose of the propensity score matching is not to perfectly predict selection into treatment but to balance all covariates. While differences in covariates are expected before matching, these would be avoided after matching. The main purpose of the PSM is that it serves to balance covariates between the two groups. Consequently, the idea behind balancing tests is to check whether the propensity score is adequately balanced or not.

The basic idea of all approaches is to compare the situation before and after matching and check if there remain any differences after conditioning on the propensity score (Caliendo & Kopeinig, 2008). Rosenbaum & Rubin (1983) emphasized that the crucial issue is to check whether the balancing condition is satisfied or not.

There are different approaches in applying the method of covariate balancing (i.e., the equality of the means on the scores and all the covariates) between treated and non-treated individuals. Among different procedures, the most commonly applied ones are described below.

Standardized bias

One suitable indicator to assess the distance in marginal distributions of the X variables is the standardized bias (SB) suggested by (Rosenbaum & Rubin, 1983). It is used to quantify the bias between treated and control groups. The standardized bias before matching is given by;

$$SB_{before} = 100.\frac{\overline{X_1}-\overline{X_0}}{\sqrt{0.5(V_1(X)+V_0(X))}} \qquad (13)$$

The standardized bias after matching is given by;

$$SB_{before} = 100.\frac{\overline{X_{1M}}-\overline{X_{0M}}}{\sqrt{0.5(V_{1M}(X)+V_{OM}(X))}} \qquad (14)$$

Where $\overline{X_1}$ and $\overline{X_0}$ are the sample means for the treated and control group respectively.

Where $X(V_1)$ and $X(V_0)$ are the mean (variance) in the treatment and control group before matching respectively, X1M (V1M) and X0M (V0M) are the corresponding values for the matched samples.

T- test

A two-sample *t*-test to check if there are significant differences in covariate means for both groups (Rosenbaum & Rubin, 1983). Before matching differences are expected, but after matching the covariates should be balanced between the two groups and hence no significant differences should be found. The *t*-test might be preferred if the evaluator is concerned with the statistical significance of the results. The shortcoming here is that the bias reduction before and after matching, is not clearly visible.

Joint Significance and Pseudo-R2

Additionally, Sianesi (2001) suggests re-estimating the propensity score on the matched sample that is only on participants and matched nonparticipants and compare the pseudo R2 before and after matching. The pseudo-R2 indicates how well the explanatory variables explain the participation probability. After matching there should be no significant differences in the covariates between the two groups and the pseudo-R2 should be low.

Sensitivity test

Recently checking the sensitivity of the estimated results becomes an increasingly important topic in the applied evaluation literatures (Caliendo & Kopeinig, 2008). In observational studies, treatments are not randomly assigned to experiment units, so that the randomization tests and their associated interval are not generally applicable. In attempt to compensate for lack of randomization, treated and control units are often matched based on observed covariates.

To confirm the robustness of the finding of ATT; the post estimation analysis of sensitivity test was checked. Sensitivity analyses examine how strong the influence ϒ (unobserved) on the participation process needs to be. If there are unobserved variables that affect participation decision and the outcome variable simultaneously, a hidden bias might arise to which the average treatment effect are not robust (Rosenbaum & Rubin, 1983).

In participation probability is given by;

$$Pi= p\ (xi,ui) = P(Di=1|xi,\ ui) = F\ (\beta xi+\Upsilon ui) \qquad (15)$$

Where Xi is the observed characteristics for an individual, ui is the unobserved variables, and ϒ is the effect of ui on participation decision. If the analysis is free of hidden bias, ϒ is zero and the participation decision will be fixed only by Xi. In case of hidden bias both groups with the same observed covariates x have different chances of receiving treatment.

Sensitivity test evaluates how program effect is affected by change in ϒ. The following bounds on the odds ratio of the participation probability of both individuals are applied.

$$\frac{1}{e^{\Upsilon}} \leq \frac{Pi(1-Pj)}{Pj(1-Pi)} \leq e^{\Upsilon} \quad (16)$$

Table 1: Description summary of variables used in the Study

Variables code	Description	Measurement	Type	Expected sign
Participation	farm households' participation in microfinance program	1 for participant and 0 for not participant	Dummy	Not applicable
Income	Annual income amount of farm households'	Birr	Continuous	+
GENDER	Sex of household head	1, If household head is male, 0 otherwise	Dummy	+
AGE	Age of household head	Year	Continuous	-
FAMSIZE	Family size of household	Number of family	Continuous	+
MARST	Marital status of household head	1, If household head is married, 0 otherwise	Dummy	+
DISTANCE	Distance of household residential from microfinance center	Minutes	Continuous	-
EDUC	Educational level of household head	Year of schooling	Continuous	+
RISKPERC	Household perception of risk	1 if positive and 0 negative	Dummy	+
FARMSIZE	Cultivated land size of household	Hectare	Continuous	+
EQUB	*Equb* membership of household head	1 if member, 0 otherwise	Dummy	+
EXTVST	Number of times household have had contact with an extension agent in one year	Number	Continuous	+
LSTOCK	Livestock owned	TLU	Continuous	-
TRAIN	Household head access to training	1, If household access to training, 0 otherwise	Dummy	+

3. Result and Discussions

The results of the descriptive statistics relied on the data collected from randomly selected participants and non-participants of microfinance program. The descriptive statistics were run to observe the distribution of the independent

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variables. Of the total sample, respondents interviewed 192(52.75%) were clients and represent the treated group while 172(47.25%) were non-clients of the program and were classified as the control or comparison group.

Table 2: Summary statistics of Continuous independent and Outcome Variables

Variables	Total sample (N=364)	Participant (N=192)	Non-participant (N=172)	Mean Difference	t-value
	Mean (Std. Dev.)	Mean (Std. Dev.)	Mean (Std. Dev.)		
AGE	40.3489 (10.867)	43.8175 (10.312)	36.4765 (10.165)	-7.341	-6.85***
FAMSIZE	4.978 (2.105)	6.37 (1.871)	3.4245 (0.943)	-2.9455	-18.65***
EDUC	0.799 (1.898)	1.495 (1.495)	0.0235 (0.152)	-1.4715	-8***
FARMSIZE	1.424 (1.027)	2.048 (1.017)	0.728 (0.396)	-1.321	-16***
DISTANCE	211.3874 (204.0901)	143.099 (65.7411)	287.6165 (269.2845)	144.5175	7.2***
EXTVST	0.8929 (1.043)	1.526 (0.971)	0.186 (0.552)	-1.34	-15.95***
TLU	7.2888 (3.3134)	7.726 (3.334)	6.801 (3.2308)	-0.925	-2.7**
INCOME	27240.93 (21865.45)	40843.75 (21328.31)	12056.40 (8193.223)	-28787.35	-16.65***

Note: ***, and ** implies level of significance at 1%, and 5%, respectively

Source: Own computation result based on survey data (2022)

Age of household head: Age is a variable that may affect participation in microfinance program. Based on the results presented in Table 2 above, the average age of the sample household head was found to be 40.3489 years. On the other hand, the average household age of the participant is 43.8175 years and the corresponding figure for non-participant is 36.4765. From the statistical analysis performed, it was found that the mean age difference between non-participant and participant in microfinance program is -7.341 years and is statistically significant at one percent probability level.

Family Size: Regarding the family size of the respondents, the average family size for the sample household is 4.978. For the participant (treated group) and non- participant (control group), the average family size is about 6.37 and 33.4245 respectively. When we compare the average family size between non-participant and participant, the study result revealed that households that participate in microfinance program have more family size than non-participant households.

The mean difference in family size between the two groups is -2.9455 and is statistically significant at one percent probability level.

Education Level (in year of schooling): Education level of farm household head is another variable that may affect participation in microfinance program. The average level of education for the sample household is 0.799. For the participant (treated group) and non- participant (control group), the average year of schooling is about 1.495 and 0.0235 grade respectively. When we compare the average schooling years between non-participants and participant, the study results show that households that participate in microfinance program have more literate than non-participant households. The mean difference in education level between the two groups is -1.4715 and is statistically significant at one percent probability level.

Farm Size: Relating to cultivated farm size of the respondents, the average farm size for the entire sample of respondents is 2.849 hectare. The average cultivated farm size for the participant (client) and the corresponding figure for non-participant (non-client) of microfinance program are 4.0965 hectare and 1.455 hectare respectively. The mean difference is -2.6415 hectares. This implies that farm households that have more cultivated farm size are more participated in microfinance programs than who have less farm size. Thus, the significance of the mean difference of cultivated land size between participant and non-participant households showed that it was found to be statistically significant at one percent probability level.

Distance: It refers to the distance between farm households' residence and the office of microfinance in the woreda and measured in minutes. The closer the household's residence to the microfinance office, the less the transportation charges, reduced walking time and reduced other marketing costs, better access to market information and facilities and better access to participate in microfinance program. The average distance of all sample respondents is about 211.3874 minutes. On the other hand, the average distance for participant and non- participant is 143.099 and 287.6165 minutes respectively. This result shows that participant households are located nearer to the microfinance office than non-participant households. The mean difference in distance between participant and non-participant is about 144.5175 minutes and the variable is negatively significant at one percent probability level.

Extension Visit: Extension visit is another variable that may affect participation in microfinance program. The average frequency of the total sample household's visited by extension service is 0.8929 times per year. While the average extension visits for the participant household and their counterpart is 1.526 and 0.186 time per year respectively. The meaning difference is -1.34. Therefore, the result of this statistical analysis indicated that farm households' those more visited by extension workers are more clients of microfinance program than those who visited less and their mean difference is statistically significant at one percent probability level.

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Table 3: Summary statistics of Dummy independent variables

Variables	Category	Total sample (N=364)		Participant (192)		Non-participant (N=172)		Chi-square
		Freq.	%	Freq.	%	Freq.	%	
GENDER	Male Female	296 68	81.32 18.68	186 6	96.88 3.12	110 62	63.95 36.05	64.73***
MARST	Married Non-married	334 30	91.75 8.25	189 3	98.44 1.56	145 27	84.30 15.70	23.97***
RISKPERC	Positive Negative	142 222	39.02 60.98	112 80	58.33 41.67	30 142	17.44 82.56	63.76***
TRAIN	Yes No	148 216	40.66 59.34	133 59	69.27 30.73	15 157	8.72 91.28	137.86***
EQUB	Yes No	160 204	43.96 56.04	136 56	70.83 29.17	24 148	13.95 86.05	119.15***

Note: *** implies level of significance at 1%

Source: Own computation result based on survey data (2022).

Livestock holding in TLU: In order to standardize livestock holdings of the sample households, TLU was calculated based on conversion factors. Based on TLU measure, the average livestock owned by the sample household is 7.288. The average livestock owned by participant and non-participant household is 7.726 and 6.801 respectively. The mean difference is -0.925. The result of these statistical analyses indicates that participant households have more livestock than non-participant households and thus livestock holding is statistically significant at five percent probability level.

Gender of household head: The survey result presented on above Table 3 above depicts that 96.88% of respondents involved in microfinance program were male household head whereas, 3.12% of respondents were female household head. This indicates that male households are more participate in microfinance program than female household heads. The result of Chi Square analysis shows that there is a significant association between the gender of household head and participation in microfinance program at one percent level of significance.

Marital status: Marital status is another variable that may affect participation in microfinance program. The attitude of society is not similar for married and non-married households about trustworthiness and loyalty. The survey also revealed that farm households that married had more chance of participating in microfinance programs than those of non-married (widowed, divorced and single). The result of Chi Square Analysis shows that there is a significant association between access to train and participation in microfinance programs at one percent level of significance.

Table 4: Logit regression results on the determinants of farm households' participation in microfinance program

Variable	Coefficient	Std. Error.	p-value	Marginal effects
GENDER	1.353	5.024	0.788	0.1823
AGE	0.08	0.056	0.155	0.0077
MARST	-0.247	3.498	0.944	-0.0222
FAMSIZE	2.917***	0.844	0.001	0.2839
EDUC	1.658*	0.9	0.065	0.1613
FARMSIZE	2.89**	1.26	0.022	0.2813
TLU	0.075	0.211	0.722	0.0073
RISKPERC	2.55*	1.394	0.067	0.2238
DISTANCE	-0.011*	0.007	0.087	-0.0011
TRAIN	5.046***	1.558	0.001	0.4823
EQUB	-0.225	1.255	0.858	0.0221
EXTVST	0.988*	0.56	0.078	0.0961
Constant	-23.903***	8.863	0.007	

Number of obs = 364

LR chi2 (9) = 474.74

Prob > chi2 = 0.0000

Log likelihood = -14.385104

Pseudo R2 = 0.9429

Note: ***, ** and * implies level of significance at 1%, 5% and 10% respectively

Source: Own computation result based on survey data (2022).

Risk Perception: The survey result showed that 60.98% of the respondents had a positive perception to accept a default risk to take loans while the remaining 39.02% had a negative perception to accept default risk to take loans. When the comparison of households between participant and non-participant was made, 58.33% of participant households do not fear to accept a default risk and 41.67% of participant households fear risk of default to take the loan and the corresponding figure for non-participant is 82.56% were fear of risk default and 17.44% was not fear risk default. The result of statistical analysis showed that there is significant association between household perception of risk and participation in microfinance program at one percent level of significance.

Access to train: Access to training enables farm households' to seek out and understand the opportunity to borrowing money from microfinance institutions. The survey result revealed that 69.27% of respondents engaged in microfinance program had access to train whereas 30.73% of respondents who were not engaged in microfinance program had no training access. The result of Chi Square Analysis shows that there is a significant association between access to train and participation in microfinance programs at one percent level of significance.

Membership in *equb*: *Equb* is a voluntary association that provides rotating credit and saving services for its members. Membership in *equb* helps households to accumulate more money for further investment that enhances participation in microfinance programs. The survey result revealed that, of the total sample households, only 43.96% are *equb* members. At the time of the survey, 70.83% of *equb* members had participated in microfinance program. The result of Chi Square Analysis shows that there is a significant association between access to train and participation in microfinance programs at one percent level of significance.

Table 4 above depicts that the study was analyzed on twelve independent variables that may influence farm households' participation in microfinance programs. Namely gender of household head (GENDER), age (AGE), marital status (MARST), Education level of household head (EDUC), family size (FAMSIZE), cultivated farm size (FARMSIZE), total livestock ownership (TLU), household perception to risk (RISKPERC), distance from microfinance institution to household home (DISTANCE), Access to training (TRAIN), *equb* membership (EQUB) and extension service (EXTVST) were incorporated in the model and jointly statistically significant on participation of farm households'' in microfinance program *i.e.,* the model as whole is statistically significant.

The pseudo R2 value of the model used to measure to what extent the independent variables explained the dependent variable. As indicated in the above table 4, Pseudo R-square with value (R2=0.9429) shows that about 94.29 percent that hinders participation of farm households in microfinance program is explained by independent variables incorporated within the model. Thus, these variables collectively have good explanatory power. While the remaining less than half percentage *i.e.* 5.71% variation in microfinance programs of farm households in the study area could be explained by exogenous variables which are outside the model.

Table 5: Result of distribution of estimated propensity score

Groups	Observation	Mean	Std. Dev.	Minimum	Maximum
All households	364	0.5275	0.4748	1.58e-21	1
Participants	192	0.9541	0.1355	0.1355	1
Non-participants	172	0.0512	0.1599	1.58e-21	0.9914

Source: Own computation result based on survey data (2022)

The logistic regression model was used to estimate propensity score matching for participant and non-participant farm households. Then after, the next step in PSM estimation is to ensure that propensity scores are balanced across treated and control group. As the propensity score is probability, it has to be in the interval [0, 1]. In setting the common support conditions, the minimum and maximum comparison was made. As shown in Table 5, the estimated propensity scores vary between 0.1354619 and 1 with a mean of 0.9541458 for participating households and between 1.58e-21 and 0.9914141 with a mean of 0.0511894 for non-participating households. Then, the common support region would lie between 0.1354619 and 0.9914141. This suggests that households whose estimated propensity scores are less than 0.1354619 and larger than 0.9914141 are not considered for the matching purpose (See Appendix 7 for its graphical representation). Because of this restriction, 140 households from participants were dropped from the analysis in estimating the average impact of participation in microfinance program.

Table 6: Performance of different matching estimators

Matching estimators		Matching Performance criteria		
		Balance test	Pseudo R2	Matched sample size
Kernel	bwidth 0.1	9	0.147	224
	bwidth 0.25	9	0.136	224
	bwidth 0.50	9	0.158	224
Nearest Neighbor	neighbor(1)	9	0.171	223
	neighbor(2)	9	0.171	223
	neighbor(3)	9	0.171	223
	neighbor(4)	9	0.167	223
	neighbor(5)	9	0.171	223
Radius or Caliper	radius caliper(0.1)	8	0.136	224
	radius caliper(0.25)	8	0.155	224
	radius caliper(0.5)	8	0.171	224

Source: Own computation result based on survey data (2022)

Different matching algorisms were used in matching microcredit participant with non-participant households in the common support region. The final choice of matching algorism is based on three criteria: namely equal mean test (balancing test), pseudo R2, and size of matched sample. Matching algorism which balances all explanatory variables (result in insignificant mean differences between the two groups), bear low pseudo-R2 value and results in large sample size is preferable (Jafer, 2014). Thus, based on these criteria as indicated in table 6, Kernel matching with bandwidth (0.1) was chosen since it balances all of the explanatory variables.

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Therefore, the impact analysis procedure was followed and shown using kernel matching with a bandwidth of 0.1.

Table 7: **Result of Propensity score and covariate balance test**

Variable	Matching Sample	Mean		Standard bias %	Reduction bias %	t-test
		Treated	Control			
GENDER	U	0.96875	0.63953	90.9		8.85***
	M	0.92308	0.99724	-20.5	77.5	-1.95
AGE	U	43.818	36.477	71.7		6.83***
	M	43.673	41.668	19.6	72.7	1.07
FAMSIZE	U	6.3698	3.4244	198.8		18.63***
	M	5.0385	4.534	34.0	82.9	3.12
EDUC	U	1.4948	0.02326	86.3		8.00***
	M	0.4615	0.29873	2.8	96.8	0.36
FARMSIZE	U	4.0964	1.4549	171.1		15.98***
	M	2.9423	3.2896	-22.5	86.9	-1.50
DISTANCE	U	143.1	287.62	-73.7		-7.20***
	M	148.85	128.22	10.5	85.7	1.75
EQUB	U	0.70833	0.13953	140.4		13.27***
	M	0.67308	0.65558	4.3	96.9	0.19
EXTVST	U	1.526	0.18605	169.8		15.9***5
	M	1.2629	1.8702	-76.1	55.2	-2.55**
TLU	U	7.7258	6.8008	28.2		2.68***
	M	7.6986	67.3225	11.5	59.3	0.63

Source: Own computation result based on survey data (2022)

As indicated in table 7 above, the t-values in the table show that before matching eleven chosen variables exhibited statistically significant differences while after matching all of the covariates are balanced.

Table 8: **Average treatment effect on the treated**

Outcome variable	Sample	Treated	Controls	Difference	S.E.	T-stat
INCOME	ATT	40843.750	12056.395	28787.355	1730.615	3.64***

Note: *** implies a level of significance at 1%

Source: Own computation result based on survey data (2022)

As shown in table 8 above, the study found that average treatment effect of the treated (ATT) on household annual income for farm households' participation in microfinance program was 28787.355 ETB. This implies that the study has found that farm households who had participated in microfinance program had increased their total income on average by 28787.355 birr per year than non-participants and was significant with t-value of 16.63 at 1 percent probability level.

The sensitivity analysis shows that the impact result estimates are insensitive to unobserved selection bias. Thus, it can be concluded that the impact estimates (ATT) are insensitive to the hidden bias and the result is pure effect of participation in microfinance program on households' income.

4. Conclusion and recommendations

Microfinance intervention is taken as a strategy to overcome the constraints of convectional bank and it is seen as one of the most efficient instruments to promote economic development, livelihood improvement, diversification, and infighting poverty among rural households. It also provides collateral free credit to rural households that lack previous rural development paradigms.

The result of descriptive statistics indicated that the majority; more than half of clients of microfinance program are allocated the taken microcredit to purchase agricultural input followed by purchase oxen, cattle fattening and for local trade. The result of logit indicated that farm households' participation in microfinance program was significantly affected by seven explanatory variables. Among the variable family size of household head, education level, farm size, risk perception, training access of household head, and extension visit affected the likelihood of participation in the program positively whereas distance of household home from microfinance office have a negative effect.

The concluding result based on PSM showed that there were significant differences in annual income of households between treated and control households, which could be attributed to the participation of microfinance program. The effect of microfinance program on annual income of farm households was higher for the participants than non-participants and was statistically significant and positive. Thus, microfinance programs have improved household livelihood through an increase in income in the study area. The result of Rosenbaum bounding procedure to check the hidden bias due to unobservable covariates showed that the estimated ATT for outcome variable was insensitive unobserved covariates indicating its robustness.

Therefore, based on the findings of this study, we have a wide range of recommendations to the improvement of the microfinance program in the country in general and Boneya Boshe district in particular. Understanding the determinants of participation in microfinance programs and its impact on the livelihoods of farm households as well as, disclosing the characteristics of the program would help all concerned bodies in general and microfinance institutions in particular to design and implement more effective policies.

Education level is found to be the important factor that enhances rural households being participant in microfinance programs. Rural households have to access education nearby their village. Therefore, the government has to strength, expand and monitor adult teaching programs.

Distance of rural households' residential from microfinance office also found to be an important factor which limits the participation of rural households in microfinance program. Therefore, governmental organizations and other stakeholders expand the proximity of infrastructure. And also, the institutions have to extend their service branch to the rural areas with quick, efficient and responsive service to those who demand their program which saves time and reduces transportation cost.

The study has found that farm households' fear of accepting a default risk in accessing loan was the factor that has been limits rural households participation in microfinance program. Therefore, microfinance institutions had better give more emphasis on changing the attitude of households associated with this problem. Moreover, the institution, governmental organization and other concerned stakeholders' have to develop risk-minimizing system and provide necessary input to overcome risk-bearing factors.

The study also found that cultivated farm size of household head affects the probability of farm households' participation in microfinance programs positively. Households who have large, cultivated farm size are more participants of the program than less cultivated farm owner is. Therefore, microfinance institutions have to create awareness of those households who own small-cultivated land size to enhance their participation in microfinance programs.

The findings of the study also found that farm households' access to training are more likely to engage in microfinance programs. Thus, giving training could be an effective instrument in increasing participation in microfinance programs. Therefore, the institutions and governmental organizations have to give special attention to encouraging the task of establishing skill training centers, which focused on participation in microfinance programs and upgrading the skills of farm households at local level is necessarily important.

Similarly, the result of the PSM indicated that microfinance program has a significant and positive impact on annual income of participant household, which motivates the non-participant household to participate and earn more income. Therefore, microfinance institutions have to broaden their outreach and expand their financial access into rural areas.

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