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Impact of Institutional Credit on Crop Productivity in Kemkem Woreda, Ethiopia

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Abstract

Among many factors that affect farm production, access to credit has been identified as important element in agricultural production. Farmers demand institutional credit to improve farm productivity, but are often denied by financial institutions. While there has been significant research on credit constraints in developing countries, there is surprisingly little information pertaining to the actual impacts of credit constraints on crop productivity. The objective of this paper is to investigate the impact of credit on crop productivity. The primary data was collected using structured questionnaires administered to individual households. Triangulation with key informant interviews, field observations, and interactive discussions with farmers and farmer groups provided information behind contextual issues underpinning the statistical inferences. A multistage sampling technique was used to select crop growers who applied for institutional credit. Propensity Score Matching is specified to estimate propensity score from the pre-treatment characteristics using binary logit model to obtain matched treated and non-treated (control) observations as inputs for impact analysis and estimate the Average Treatment Effect on Treated (ATT).The results offer the strong and positive impact of institutional credit on crop productivity implying that credit enables the farmers to purchase superior quality or high yield variety seeds, fertilizers and pesticides and agricultural yield increases because of timely and adequate inputs. Thus, the study recommended in time provision of appropriate amount of loan for the enhancement of crop productivity in the study area.

Key words: *credit, productivity, Propensity Score, impact, Ethiopia*

1. INTRODUCTION AND BACKGROUND

A crucial challenge Africa economy facing is deep rooted in the agricultural sector's underdevelopment (Zeller 1994). The failure continues to be related to the "failure to invest in the productivity of its farmers" Researchers' and policy makers generally agreed that the poor rural households in developing countries lack adequate access to credit. Lack of adequate credit access has statistically negative consequence for various aggregate and household-level outcomes, including; technology adoption, agricultural productivity, food security, nutrition, health and overall household welfare as its availability allows both greater consumption and greater purchased input use, and thus increases welfare of the farmers (Awunyo-Vitor, Abankwah et al. 2012). The availability of microcredit, broadly defined as the provision of financial services such as savings and credit to the poor household is a necessary but not sufficient condition for rapid poverty reduction (Guirkinger and Boucher 2008).

The agriculture growth depends very much on improvement of infrastructural facilities, supply of enhanced irrigation water, land reclamation, transpiration, mechanical power and other critical form inputs like seeds, pesticides and fertilizers (Kashif, Zafar et al. 2016). In Ethiopia Agricultural credit assumes even a central position in the whole strategy of agricultural development of a country for a number of reasons. As a result, farmers' credit needs have increased considerably due to modernization in agriculture sector over the past few decades. Currently the main formal credit sources consist of financial institutions such as commercial banks, and cooperative societies (Ali, Deininger et al. 2014).

Agriculture is characterized by the small farms with an average of 1 hectare having low income negligible saving and low capital formation to undertake latest agriculture technologies. (Anríquez and Stamoulis 2007). A severe drought or flood may destroy capabilities of small farms to sustain even normal production cycle for years resultantly they cannot exploit the potential of their land to the optimum level and thus fail to achieve higher yield per acre. Farming requires capital like other business for its farm operations. Timely availability of capital leads to adoption of improved seeds, fertilizers and modern technologies which increase the farm production and ultimately the growth rate (Kassie, Jaleta et al. 2013; Mazvimavi and Twomlow 2009).

One of major constraints for small-scale farmers to adopt agricultural technologies is credit (Croppenstedt et al.,2003; Flory 2012; Larson and Zerfu 2010) since cash resources are generally insufficient to cover high-yielding variety seeds and chemical fertilizer purchase for small-scale farmers at the planting season. Despite the importance of credit, the private financial sector is underdeveloped especially in rural areas due to high and correlated risks in smallholder agriculture, asymmetric information between borrower farmers and credit providers as well as incomplete enforcement of credit contracts (Kuhn, Darroch et al. 2000). To this end, the study evaluates the impact of the credit scheme on crop productivity.

2. REVIEW OF THE RELATED LITERATURE

2.1. Key Concepts, Terms, and Definitions

Balance test: it a means to find all variables regressed variables insignificant after testing propensity score to reduce the influence of confounding variables (Austin, 2011). Its objective is to verify that treatment is independent of unit characteristics after conditioning on observed characteristics (Caliendo & Kopeinig, 2008).

Comparison group: group often established by taking a controlled group identical to the treatment group in observable characteristics, except that it is not subjected to the intervention (Caliendo and Kopeinig, 2008).

Impact assessment: it is a process of systematic and objective identification of the short and long term effects of intervention on economic, social, institutional and environments. Such effects may be anticipated or unanticipated and positive or negative, at the level of individuals, households, or the organization caused by ongoing or completed development activities such as a project or program (Mahmoudi, Renn et al. 2013).

Propensity score (PS): is a measure of the probability of an observation receiving the conservation program, given a vector of covariates" estimated as a function of individual characteristics using logit or probit model (Rosenbaum, 2010).

Treatment group: the group of people, firms, facilities or whatever who receive the intervention. It is also called participants (Caliendo and Kopeinig, 2008).

Selection bias: it is a misleading result that creates a threat to the validity of the program effect estimate in any impact assessment using a non-equivalent comparison group. This bias commonly occurs when the comparison group is ineligible out of treatment (Delmotte, Lacombe et al. 2013).

2.2. Empirical Literatures

The existing literature in an assessment of credit impact on crop productivity largely employ propensity score matching techniques as appropriate means of analyzing impact of institutional credit on crop productivity. For instance, the study conducted to assess the effect of microfinance to the Millennium Development Goals (MDGs) using survey data obtained from clients of a microfinance bank, Khushhali Bank, in 2005 employ Propensity Score-Matching Methods to address the selectivity bias. The method found that the lending program contributed significantly to income generation activities such as agricultural production and, in particular, one of Millennium Development Goal 1 of animal rearing. However, the impacts on other MDGs-education, health, and female empowerment were of limited significance. This is due partly to the fact that 70 per cent of the Bank's clients in the survey went through only one loan cycle, so the impacts on other MDGs are yet to be realized (Holvoet 2006).

Getnet and Anullo (2012) employ matching technique to assess the effect of Agricultural cooperatives on livelihood development and poverty reduction in Sidama zone, Ethiopia with particular emphasis on rural household income, saving, agricultural input expenditure and asset accumulation as outcome variables. In recognition of such roles of cooperatives, Ethiopia showed a renewed interest in recent years in promoting cooperative sector development. However, there is lack of a wider and systematic analysis to produce sufficient empirical evidence on the livelihood development and poverty reduction impacts of cooperatives in the country. The finding shows that cooperatives improved the livelihoods of service user farmers through impacting better income, more savings and reduced input costs.

Study conducted to evaluate the effect of the credit guarantee policy by comparing a large sample of guaranteed firms and matched non-guaranteed firms from 2000 to 2003, adopted propensity score matching methodologies. The Results suggest that credit guarantees influenced firms' ability significantly to maintain their size, and increase their survival rate, but not to increase their investment and hence, their growth in productivity(Oh, Lee et al. 2009).

2.3. Propensity Score Model Specification

The first step in estimating the treatment effect is to estimate the propensity score. To get propensity scores binary logit estimated the logit model, with the dependent variable is decision to adopt CFT which takes a value of 1 if household adopt it and; 0 otherwise (Bergès-Sennou et al., 2007). The logit model formulated as (Gujarati and Porter, 1999):

$$Y = \alpha + \beta_1 X_1 + \beta_2 X_2 + \ldots\ldots\ldots \beta_k X_k + \varepsilon \ldots\ldots 1$$

Where:

Y = the probability of household participating in a program (CFT adopter); = Intercept (constant) term; Coefficient of the explanatory variables, Xi = Explanatory Variables; = disturbance (stochastic) term.

Choice of matching estimators: Propensity score estimation was followed by choosing between different matching estimators. Various algorithms have been invented in which propensity scores of the treatment and control observations are selected and matched on the basis of some tolerance level, weights, strata or neighborhood (Dehejia, 2005).

Checking overlap conditions and common support: Common support refers to the overlap area between the propensity scores of treatment and control groups. The goal of these sorts of techniques is to exclude treatment cases at the outset those that are beyond the observed minima and maxima of the probability distributions of the variables among control cases and vice versa (Khandker, Koolwal, & Samad,2010).

Testing Matching quality: This can be accomplished through balancing the distribution of all relevant in both treated and comparison groups or by comparing the situation before and after matching (Caliendo & Kopeinig, 2008).

The Pseudo-R2 will serve to demonstrate how well the regressors 'X's explain the probability of household participation assuming that no systematic difference in treatment and control group distribution should occur after matching. Hence the Pseudo-R2 after matching should be fairly low (Caliendo & Kopeinig, 2005).
ATT estimation is the last and impact indicator steps of the program. Baker (2000), and Heckman, Smith, & Clements (1997) empirically specified PSM with reliable and low bias estimates of the program or policy impact. Estimating participating program effect on a given outcome (Y) is specified as:

$$Ti = Yi\ (Di = 1) - Yi\ (Di = 0) \ldots\ldots 6$$

Where:

Ti = treatment effect; Yi = the outcome on household i and Di = whether household has got the treatment or not i

According to Heckman (1997), the most commonly used average treatment effect estimation is an ATT specified as:

TATT= E(T|D=1)= E [Y (1) |D =1]- E[Y(0) |D =1] ……………………………….7

As the counterfactual mean for those being treated, E[Y (0)|D =1] is not observed, one has to choose a proper substitute for it in order to estimate ATT. One may think to use the mean outcome of the untreated individuals, E[Y (0)|D = 0] as a substitute to the counterfactual mean for those being treated, E[Y(0)D =1]. However, this can't be a reality in non-experimental studies since it is likely that components which determine the treatment decision also determine the outcome variable of interest. Hence, the outcomes of individuals from treatment and control group would differ even in the absence of treatment leading to a self-selection bias. By rearranging and subtracting E [Y (0)|D = 0] from both sides of equation 7, ATT specified as:
E [Y (1)|D =1] - E[Y (0)|D = 0] =TATT + E[Y (0)|D =1] - E[Y (0)|D = 0]…………..7

From the above equation, both terms in the left hand side are observables and ATT can be identified, if and only if E[Y (0) D =1]- E[Y(0)D = 0] = 0. This condition can be ensured only in a randomized experiment. In non-experimental studies, one has to introduce some identifying assumptions to solve the selection problem using two strong assumptions as.

Assumption 1: Conditional Independence Assumption (CIA)- It states that once the observable factors are controlled for random participation it should be uncorrelated with the outcome variables (Smith & Todd, 2005).This assumption is formulated as:

Y0 Y1 ^ D|X, ………………………………………………………………… 8
Where:
-independence; X - a set of observable characteristics Y0- non-adopter and; Y1- adopters.

Given a set of observable covariates (X) which are not affected by treatment conditional independence the assumption implies that the selection is only based on observable characteristics (X) and variables that influence treatment assignment and potential outcomes are at the same time observed (Caliendo & Kopeinig, 2005).

Assumption 2: Assumption of Common Support: According to DiPrete, & Gangl (2004), imposing a common support condition ensures that any combination of characteristics observed in the treatment group can also be observed among the control group. Given the above assumptions, the PSM estimator of ATT can be written as:
TATT = E [Y1 -Y0|D = 0, P(X)] = E [Y1|D =1, P(X)] - E (Y0|D = 0, P(X)] ……..8
Where:
P(X) = the propensity score computed on the covariates X.

The above equation shows that the PSM estimator is the mean difference in outcomes over the common support, appropriately weighted by the propensity score distribution of participants (Rosenbaum and Rubin, 1983). This is to ensure that persons with the same X values have a positive probability of being both participants and non-participants though it doesn't have power against certain alternatives (Heckman et al., 1999). Hidden bias strength could be captured by the parameter Γ, and where Γ = 1 no hidden bias exists (Caliendo & Kopeinig, 2005). Rosenbaum bound method assumes an unmeasured covariate (ui) that affects the probability of program participation. If P (xi) is the probability that the ith individual participate in a program, and xi is the vector of observed covariates, then the probability of participating a program is given by:

$$P(x_i u_u) = p(d_i, = 1 | x_i, u_i) = F(\beta x_i + \gamma u_i) \ldots\ldots\ldots\ldots\ldots 9$$

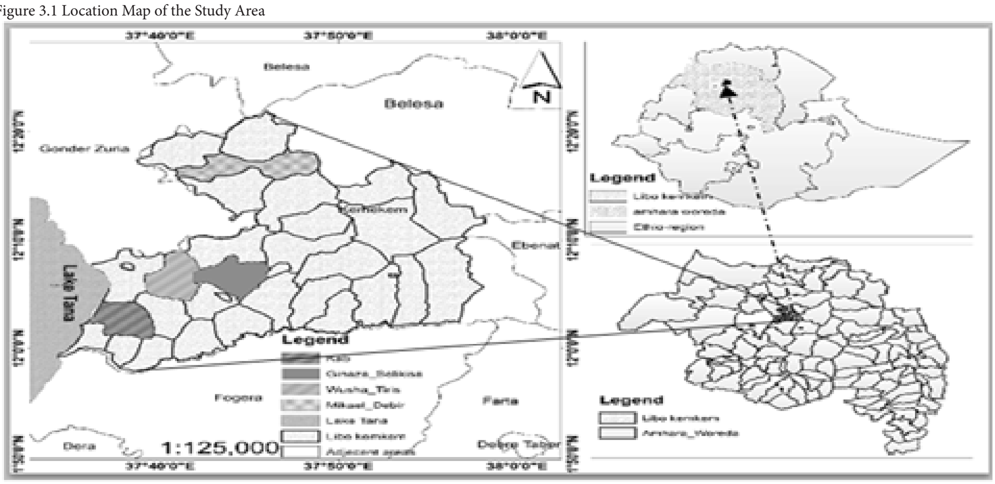
3. DATA AND METHODS

3.1. Description of the Study Area

The study was conducted in Kemem woreda found in South Gondar Zonal admin of Amhara National Regional State of Ethiopia. As depicted below, Kemkem is one of the woreda in the Amhara Region of Ethiopia. It is one of the 113 Woredas of Amhara Region, divided in to 29 rural and 4 urban Kebeles (CSA, 2011). The landscape is mountainous and plain low land and part of lowland of the Woreda is partly covered with Acacia trees and the soil is black which cracks deeply during the dry season(Asmamaw, Alemu et al. 2013). Small-scale irrigation is started in the plain low land part of the Woreda(Chanie, Dejen et al. 2012). It is located in Ethiopia about 620 km north of Addis Ababa, the country's capital town. Kemekem woreda is part of the Debub Gondar Zone, bordered on the south by the Reb which separates it from Fogera, on the west by Lake Tana, on the north by the Semien Gondar Zone, and on the east by Ebenat (Dea 2016).

The administrative center is Addis Zemen; other towns include Amba Meda and Yifag. Rivers in this woreda include the Arno and the Reb, which drain into Lake Tana (CSA, 2011). A survey of the land in this woreda show that 51% is arable or cultivable, 8.3% pasture, 5.9% forest or shrub land, 17.98% covered with water, and the remaining 17.03% is considered degraded or other (Sisheber, Fente et al. 2015).

Figure 3.1 Location Map of the Study Area



Source: Central Statistical Agency of Ethiopia (2011)

3.2. Data Requirements, Sources and Methods of Collection

Primary and secondary data was collected to identify the different variables considered to be key thresholds and capture the necessary interactions, viz, socio-economic, demographic, institutional attachments of household head. These independent variables served as determinants of credit access. The study utilizes secondary data collected from different sources depending on availability of data and interest of the study. The sources include various second-hand data obtained from published and unpublished document. These resources were used to describe the study area and obtain ideas to explore empirical literature and specify relevant econometrics models.

The field survey was held at farm household level. The data collected had been cross-sectional in nature. Detailed and structured survey questionnaires were designed specifically to elicit responses about credit access and how it has impacted crop productivity. Discussion with farmers and agricultural extension staff was made to generate information. Key informants were used as information source to conduct preliminary assessment of the study and the study population.Sampling techniques.

Study sites and study units were selected using multistage (four stage) purposive, and stratified, systematic and random sampling techniques, respectively. Study sites and study units were selected using multistage (five stage) purposive and stratified systematic random sampling techniques, respectively. The first stage involved a purposeful selection of Kemkem Woreda as a study area. In the second stage, the study Woreda was stratified purposively into highly; medium and low user status of institutional credit based on data available in Amhara Credit and Saving institution and Woreda Agricultural and Rural Development Office.

A total of 13 kebeles were identified as credit users. Based on the data obtained, 6 kebeles were rated as highly user of formal credit. While number of kebeles rated at medium and low credit user status were 4 and 3, respectively. In the third stage, kebele were selected randomly in each category. Accordingly, Buro_Teraroch and Awzet Azawur kebele were identified among the kebele rated as high credit users' kebeles. Girbi and Debelima kebele were each selected randomly from the later two categories, respectively.

In the fourth stage 853 household heads which comprise 403 credit users and 450 non-user of credit were identified purposively as a target population. Among them fifty farmers who were credit users were female headed household (LWARDO, 2016).

Required sample size from targeted population in the villages compute appropriate sample size, the level of precision, the level of confidence or risk, and estimation of the degree of variability in the attributes were measured and determined using the formula (Krejcie and Morgan, 1970) from below as:

$$S = \frac{\chi^2 * N * P(1-p)}{\left(ME^2 * (N-1)\right) + \left(\chi^2 * P * (1-P)\right)}$$

Where:
S = required sample size; c2 = table value of chi-square for 1 degree of freedom at the desired confidence Level (3.841); N = the population size; P = the population proportion (assumed to be 0.50 so as to maximum sample size) and; ME= Desired Margin of Error (expressed as a proportion, 0.035 at 95 % CI).

Table 3.1 Distribution of Sample Kebeles and Household Sample Size

Selected RKAUs	Targeted Number of household	Sampled households				
	Credit User	Non-Credit user	Total	Credit User	Non-Credit users	Total
Ginaza Selikisa	132	153	285	22	33	55
Kab	101	123	224	34	48	82
Wusha_Tiris	84	95	179	49	44	93
Mikael_Debir	86	79	165	20	30	50
Total	403	450	853	125	155	280

Source: Sample size computation, 2017

Sample size computation considered financial resource available and adequacy of other resources such as trained manpower and time (Safavian and Landgrebe 1991; Levy & Lemeshow, 2013). In the fifth stage, those 280 households' sampled were picked using systematic sampling techniques at every Kth individual, where k refers to the sampling interval.

4. EMPIRICAL RESULTS AND DISCUSSIONS

4.1. Results of Descriptive Analyses

This section describes selected characteristics of institutional credit users compared to non user of the credit, regardless of their location. However, it should, be noted that mean difference comparisons may not take into consideration other farmers characteristics which may compound credit use decision and its impact on crop productivity with the influence of other characteristics.

Table 4.1 Summary Statistics of Important Variables

Variables	Description	Credit Users	Non-Credit users	ttest /χ^2 value
Predicted	Dependent/outcome Variables			
LOGCropr	Crop Productivity (kg/ha farmland) in logarithm form	3.6955	3.6441	-2.65 **
CredAcc	Household access credit (1 if yes)	0.45	0.55	
covariates	Pre-treatment Variables			
WorConRat	Household member in working age to consumer	1.129	1.090	-0.273
Hhsize	Number of household members	7.326	7.437	0.630
PrNOwL	Privately owned land size in hectare	1.08	1.07	-0.07
CoAsMem	Household is member of cooperative association, 1 if yes	151	129	0.9749
OxenNoper	Number of oxen owned per ha of farmland	0.388	0.401	0.4499
MoAgriTec	Household is user of modern agricultural technology, 1 if yes	151	129	0.7022
Cropla	Cropped land size in hectare	1.297	1.286	-0.1422
ME	Family Labor Force in Man Equivalent	2.62	2.33	-0.96
OnofffAct	Household engaged in on/off farm activities, 1 if yes	151	129	0.087
Proprcrla	Proportion of cropped land in percent	58.718	53.111	-1.576*
AgeSquared	Square of Household age in years	1717.47	1728.96	0.094
IrlanOwner	Irrigable land ownership status, 1 if owned irrigable land	151	129	1.817

Source: Sample size computation, 2017

Note. ***P < 0.01, *p < 0.1

Mean of credit users' proportion of cultivated land statistically varied from non- credit users positively at less than 10 per cent level of significance. The variable is used as a propensity score. No significant variation in mean of other pre-treatment characteristics than the noted variable (proprcrla) observed between the two groups of the households.

4.2. Results of Econometric Analysis

Propensity Score Matching is initially discussed through estimating average treatment effect on the treated as an outcome of interest using binary Logit model. Prior to estimating the model, covariates was indentified based on theoretical explanations and empirical literature on credit impact studies and authors' knowledge of the study area (Diamond and Sekhon 2013). This was made to find and estimate propensity scores. Based on matches of these scores estimated, matching estimators were selected to find out the impact or outcome variable under consideration as a result of institutional credit use decision on the mean values of the outcome variables.

4.2.1. Propensity Score Estimation Procedure

A head of executing binary logistic regression model, cross-sectional data problems were tested based on econometric assumption, whether it is holding valid for severe multicollinearity of continuous and discrete explanatory variables (Gujarati and Porter 1999). Dependent variable is a dummy taking a value of 1 if the household is a credit user; and 0 otherwise; and household pre-treatment characteristics. Variation Inflation Factor of 13 continuous variables tested within range of 1.02 to 2.56 and overall VIF of 1.32 indicating the non-existence of multicollinearity. The remaining four discrete variables regressed with Contingency coefficient ranging from 0.00572 to 0.02541, which is much less than 0.75 confirming absence of association problem (Gujarati and Porter 1999; Malhotra, Hall et al. 2006; Saunders 2011).

Table 4.2 Binary Logit Model to predict the probability of credit access on selected observables

Covariates	Coef.	Robust Std. Err.	z	P>|z|
WorConRat	0.0232	0.0666	0.35	0.728
Hhsize	-0.0474	0.2447	-0.19	0.846
PrNOwL	-0.0175	0.0725	-0.24	0.809
OxenNoper	0.0495	0.0931	0.53	0.595
AgeSquared [1]	0.2062	0.1706	1.21	0.227
MoAgriTec	0.0056	0.0033	1.7	0.088
Cropla	0.0000	0.0001	-0.24	0.808
CoAsMem	-0.0120	0.0942	-0.13	0.899
OnofffAct	-0.1379	0.1539	-0.9	0.37
Proprcrla	-0.0178	0.1981	-0.09	0.929
ME	0.1753	0.2053	0.85	0.393
IrlanOwner	-0.2018	0.1788	-1.13	0.259
Constant	-0.4822	0.5884	-0.82	0.413
No. of obs= 280 Wald chi2(13) = 142.55, Prob > chi2 = 0.000				

Source: Model Estimation Result based on data collected in the field, 2017

Note: The Square of household age in years (AgeSquared) is regressed to accurately model its effect at a differing ages rather than assuming the effect is linear for all ages

As indicated in Table 4.3, propensity score is estimated using binary logit to obtain the Average Treatment effect on Treated (ATT) via matching treated and non-treated observations as inputs for impact analysis. The matching process attempts to make use of the variables that capture the situation before the start of the intervention. Good match for the study between the two groups of household (credit users and non-users) having pre-treatment characteristics found with low R2 value (Pradhan & Rawlings, 2002).

According to Caliendo and Kopeinig (2008), there should be no systematic differences in the distribution of covariates between both groups after matching and hence, the pseudo- R2 should be fairly low. The maximum likelihood estimates of this logistic regression model show that household size influenced farm household decision to access credit and outcome of interest directly at less than 1 percent level of significance.
Once propensity scores have been computed, one needs an algorithm to match credit users in the treated group with those household to non credit users of control group, based on the closeness of their propensity scores. Several matching algorithms, such as NNM, caliper matching and kernel matching (Heckman, Ichimura et al. 1997; Smith & Todd, 2005), have been suggested in the literature section.

Matching estimators work under the assumption that a convincing source of exogenous variation of treatment assignment does not exist. The choice of such matching estimator is decided based on the balancing qualities of the estimators. According to Dehejia and Wahba (2002), the final choice of a matching estimator was guided by different criteria such as equal means test referred to as the balancing test, low pseudo-R2 and large matched sample size. Balancing test was conducted to know whether there is statistically insignificant difference after matching in the mean value of pre-treatment characteristics of the two groups of the respondents.

Table 4.3 Performance Measures of Matching Estimators

Matching algorithms	Balance test	Pseudo R^2	Mean Bias	Matched sample size
NNM with replace ment- 1 neighbor	6	0.280	26.1	280
2 neighbors	4	0.144	19.2	280
3 neighbors	6	0.159	18.5	280
4 neighbors	7	0.128	17.6	280
Nearest Neighbor Matching(NNM)without Replacement	10	0.020	7.5	280
Radius Caliper matching (epan)With no BW	6	0.280	26.1	280

Bandwidth(BW) 0.01	6	0.280	26.1	271
0.05	7	0.343	28.7	271
0.1	5	0.343	28.7	271
Kernel Matching (Normal)With no BW	12	0.017	5.4	278
Kernel Matching (Normal) With BW 0.01	12	0.012	4.9	278
0.08	12	0.017	5.4	277
0.1	12	0.017	5.8	280
0.25	12	0.017	5.8	280
0.5	12	0.017	5.8	280

Source: Evaluation of matching algorithm based on data collected in the field, 2017

After matching, matching estimators were evaluated whether the treated and control observation lies in commonly support region. Following selection of best matching algorithm indicated in shaded row of Table 4.4, the balancing powers of the estimations before T-value was ascertained by the reduction in the mean standardized bias between the matched and unmatched households, and equality of means using t-test and chi-square test for joint significance of the variables (Caliendo & Kopeinig, 2008).

Table 4.4 Balance Test for Propensity Score and Covariates

Covariates	Before matching	After matching				
	Treated	Control	T-Value	Treated	Control	T-Value
WorConRat	1.1292	1.0905	0.27	1.1108	1.1953	-0.51
OxenNoper	.38791	.40589	-0.45	.40208	.40798	-0.13
Hhsize	7.3256	7.4371	-0.63	7.35	7.3187	0.18
PrNOwL	1.1667	1.1093	0.61	1.1812	1.0988	0.78
Cropla	1.2965	1.2864	0.14	1.2271	1.2465	-0.26
Proprcrla	58.718	53.111	1.58	59.85	59.85	-0.00
AgeSquared	1717.5	1729	-0.09	1701.2	1702.3	-0.01
ME	2.622	2.6332	-0.07	2.5813	2.6021	-0.12
CoAsMem	.50388	.56291	-0.99	.50833	.53423	-0.40
OnofffAct	.17829	.19205	-0.29	.175	.15713	0.37
MoAgriTec	.6124	.56291	0.84	.58333	.56069	0.35
IrlanOwner	.4031	.48344	-1.35	.38333	.47446	-1.43

Source: Model Estimation Result based on data collected in the field, 2017.
Note: *** means significant at or less than 1 percent levels of significance

This was deliberately made to verify that treatment is independent of unit characteristics after conditioning on observed characteristics. The low Pseudo R2 indicated in Table 4.5, after chi-square test for the joint significance of variables supports hypothesis that both groups have the same distribution in covariates X after matching.

Table 4.5 Chi-Square Test for the Joint Significance of Variables

Sample	p>chi^2	Pseudo R^2	LR chi2	Median Bias	Mean Bias
Unmatched	8.09	0.021	0.778	7.3	6.3
Matched	4.05	0.012	0.983	4.9	3.9

Source: Model testing Result based on data collected in the field, 2017

As depicted in Figure 4.1, the bias distributed across each pre-treatment characteristic after matching brought the standardized mean bias, indicated in Table 4.5, to average of about 4.9, is less than 5 percent. This is sufficient as supported by most empirical studies (Smith & Todd, 2005) to assess the distance in marginal distributions of the X-variables as suggested by Rosenbaum (2002).

A substantial region of overlap indicated numerically in Table 4.3 implies the absence of common support problem. This is based on the minima and maxima approach of common support region identification (Caliendo and Kopeinig, 2008). Figure 4.2 used to depict overlap region using propensity score distribution via histogram show treated cases in dark grey on top and control cases in light grey on bottom. Two treated cases (credit users) marked in histogram as black is discarded as their propensity score is larger than the maximum in the opposite group implying a high chance of getting good matches and a large number of matched sample size from the distribution of the propensity score. The distribution of propensity score of credit users (treated) and non-users (comparison) groups slightly skewed to the right and left, respectively. The distribution for all respondents is relatively nearer to normal distribution.

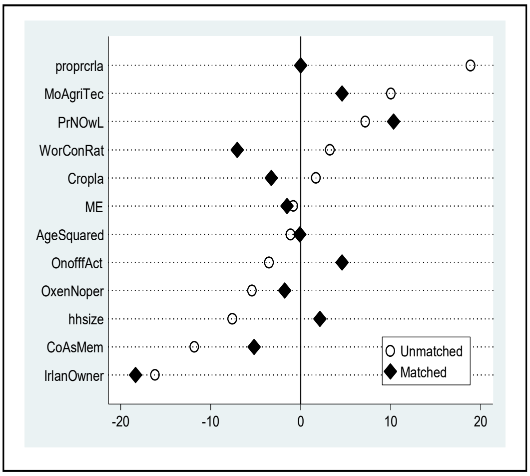


Figure 4.1: Standardized % bias across covariates
Source: Own depiction based on data collected, 2017

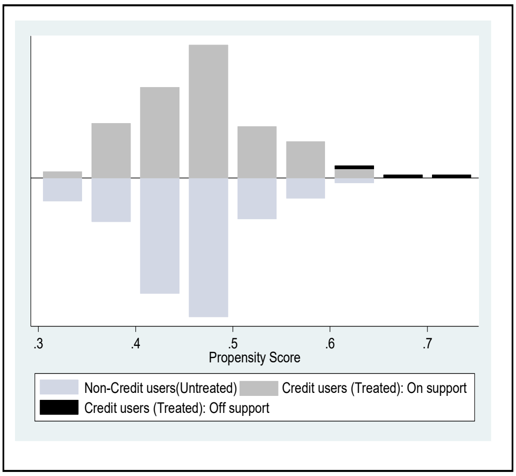


Figure 4.2: Propensity Score distribution
Source: Own depiction based on data collected, 2017

Once the propensity scores for all households (credit users and non-users) obtained using binary logit estimation, common support condition identified within range between 0.297103 and 0.392085 with mean of propensity scores of 0.464783. The probability of being non-user of credit ranges from 0.290695 and 0.649588 with the mean probability of 0.454409. The probability of being credit users ranges from 0.30351 and 0.784169 with the mean probability of 0.475157.

Ultimately, Kernel matching (normal) matching estimator with all variable mean balanced or explanatory variables balanced or insignificant, and relatively low pseudo R2 value of 0.012 and the insignificant likelihood ratio tests with large matched sample size, is preferred as best matching estimator.

4.2.2. Impact Estimate on Crop Productivity

In estimating the average treatment effects on the treated, propensity scores generated from above are used to evaluate the effect of credit between two groups of household having similar observed characteristics. T-value indicated in Table 4.6 is an indication of evaluating impact of credit on crop productivity showing that formal credit user on average has brought statistically significant and positive difference on crop productivity. The result is consistent with the findings of Ngore (2010) who found improvement in productive performance in Kenya among those who were borrowers of micro-finance credit as analyzed using propensity score matching technique, correcting for sample selection bias.

Table 4.6 Estimation of the Impact of Institutional Credit using ATT

Outcome Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
LOGCropr	Unmatched	3.69556	3.64418	0.05138	0.01942	2.65
	ATT	3.70704	3.64923	0.057812	0.02073	2.79

Source: Model Estimation Result based on data collected in the field, 2017.

4.2.3. Sensitivity of the Evaluation Results

Table 4.7 reveals the sensitivity analysis of the outcome ATT values to the dummy confounder. This has been undertaken whether conditional independence assumption was affected by the dummy confounder or the estimated ATT is robust to specific failure of the conditional independence assumption.

Table 4.7 Rosenbaum Bound Sensitivity Analysis Test for Hidden Bias

Gamma	=1	=1.05	= 1.1	=1.15	=1.2	= 1.25	= 1.3	1.4	1.45	=1.5
Sig+ (upper bound)	2.8e-06	8.0e-06	0.000021	0.00005	.00011	.000224	.000429	.001338	.002202	.00348
sig -(lower bound)	2.8e-06	8.9e-07	2.8e-07	9.0e-08	2.8e-08	8.8e-09	2.7e-09	2.6e-10	7.9e-11	2.4e-11

Source: Computation of model sensitivity result to unobserved variables, 2017

Note: gamma () - log odds of differential assignment calculated due to unobserved factors

The result showed that the inference for the impact of credit is not changing though credit users and non-users allowed to differ in their odds of being treated in terms of unobserved covariates (Rosenbaum, 2010). This implied that for all outcome variables estimated, at the various critical level of e^{γ}, the p-critical values are significant which indicate the study further have considered important covariates that affected both credit access and outcome variables. Hence, it can be concluded that credit impact estimation (ATT) is insensitive to unobserved variables and are a pure effect of being formal credit user.

5. SUMMARY AND POLICY CONCLUSION

An impact of credit on crop productivity is estimated using cross-sectional data and propensity score matching technique to address the selectivity bias. Descriptive analysis indicates that credit users' proportion of cropped land size on average statistically and positively varied from noncredit users. The analysis using average treatment effect on treated as vital impact assessment variable suggests that institutional credit has statistically a positive impact on crop productivity. This could provide a clue that credit is an important tool for improving agricultural productivity. From a policy point of view, the results confirm that credit constraints can significantly affect crop productivity and hence government should increase effort to have better chances of receiving formal credit from lending institutions to access credit timely than their present situation and purchase improved agricultural inputs before the onset of the crop growing season.

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References

Ali, D. A., et al. (2014). "Credit constraints and agricultural productivity: Evidence from rural Rwanda." Journal of Development Studies 50(5): 649-665.

Anríquez, G. and K. G. Stamoulis (2007). "Rural Development and Poverty Reduction: Is Agriculture Still Key?" eJADE: electronic Journal of Agricultural and Development Economics 4(853-2016-56113): 5.

Asmamaw, T., et al. (2013). "Prevalence of malaria and HIV among pregnant women attending antenatal clinics at felege hiwot referral hospital and Addis zemen health center." Int J Life Sci Biotechnol Pharma Res 2: 1-13.

Austin, P. C. (2011). "An introduction to propensity score methods for reducing the effects of confounding in observational studies." Multivariate behavioral research 46(3): 399-424.

Awunyo-Vitor, D., et al. (2012). "Women participation in microcredit and its impact on income: a study of small-scale businesses in the Central Region of Ghana." American Journal of Experimental Agriculture 2(3): 502-515.

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

Chanie, M., et al. (2012). "Prevalence of Cattle Schistosomiasis and Associated Risk Factors in Fogera Cattle, South Gondar Zone, Amhara National Regional State, Ethiopia." Journal of Advanced Veterinary Research 2(3): 153-156.

Croppenstedt, A., et al. (2003). "Technology adoption in the presence of constraints: the case of fertilizer de mand in Ethiopia." Review of Development Economics 7(1): 58-70.

CSA.(2011). A Study on the Use of GIS in Statistical Offices in Ethiopia Central Statistical Agency. Addis Aba ba: Ethiopian Central Statistical Agency.

Dea, M. (2016). "The Prospectus, Challenges and Causes of Gender Disparity and Its Implication for Ethiopia's Development: Qualitative Inquiry." Journal of Education and Practice 7(4): 24-37.

Dehejia, R. H., & Wahba, S. (2002). Propensity score-matching methods for nonexperimental causal studies. Review of Economics and statistics, 84(1), 151-161.

Delmotte, S., et al. (2013). "Obstacles, levers and impacts of organic farming development in Camargue." In novations Agronomiques 32: 213-226.

Diamond, A. and J. S. Sekhon (2013). "Genetic matching for estimating causal effects: A general multivariate matching method for achieving balance in observational studies." Review of Economics and statistics 95(3): 932-945.

Flory, J. A. (2012). Formal Savings Spillovers on Microenterprise Growth and Production Decisions Among Non-Savers in Villages: Evidence from a Field Experiment(No. 323-2016-11532).

Getnet, K. and T. Anullo (2012). "Agricultural cooperatives and rural livelihoods: Evidence from Ethiopia." Annals of Public and Cooperative Economics 83(2): 181-198.

Guirkinger, C. and S. R. Boucher (2008). "Credit constraints and productivity in Peruvian agriculture." Agri cultural Economics 39(3): 295-308.

Gujarati, D. N. and D. C. Porter (1999). Essentials of econometrics, Irwin/McGraw-Hill Singapore.

Kashif, A. R., et al. (2016). "Impact of Agricultural Credit and its Nature on Agricultural Productivity: A Study of Agriculture Sector of Pakistan." Journal of Environmental & Agricultural Sciences 9: 59-68.

Heckman, J. J., et al. (1997). "Matching as an econometric evaluation estimator: Evidence from evaluating a job training programme." The Review of Economic Studies 64(4): 605-654.

Holvoet, N. (2006). "The differential impact on gender relations of 'transformatory'and 'instrumentalist'wom en's group intermediation in microfinance schemes: A case study for rural south India." Journal of International Women's Studies 7(4): 36-50.

Kassie, M., et al. (2013). "Adoption of interrelated sustainable agricultural practices in smallholder systems: Evidence from rural Tanzania." Technological forecasting and social change 80(3): 525-540.

Krejcie, R. V. and D. W. Morgan (1970). "Determining sample size for research activities." Educational and psychological measurement 30(3): 607-610.

Kuhn, M., et al. (2000). "Improving the provision of financial services to micro-entrepreneurs, emerging farm ers and agribusiness: Lessons from KwaZulu-Natal." Agrekon 39(1): 68-81.

Larson, D. F. and D. Zerfu (2010). Incomplete Markets and Fertilizer Use: Evidence from Ethiopia, The World Bank.

Levy, P. S., & Lemeshow, S. (2013). Sampling of populations: methods and applications. John Wiley & Sons.

LWARDO (2016). Annual Report of Farta Woreda Agricultural and Rural Development, Libo Kemkem Wore da (Unpublished).

Mahmoudi, H., et al. (2013). "A framework for combining social impact assessment and risk assessment." Environmental Impact Assessment Review 43: 1-8.

Malhotra, N., et al. (2006). Marketing research: An applied orientation, Pearson Education Australia.

Mazvimavi, K. and S. Twomlow (2009). "Socioeconomic and institutional factors influencing adoption of con servation farming by vulnerable households in Zimbabwe." Agricultural systems 101(1-2): 20-29.
Ngore, P. M. (2010). Evaluation of Factors Influencing Value Addition by Butchery Agribusinesses in Igembe North District, Kenya.
Oh, I., et al. (2009). "Evaluation of credit guarantee policy using propensity score matching." Small Business Economics 33(3): 335-351.
Pradhan , M., & Rawlings, L. B. (2002). The impact and targeting of social infrastructure investments: Lessons from the Nicaraguan Social Fund. The World Bank Economic Review, 16(2), 275-295.
Rosenbaum, P. R. (2002). Observational studies. In Observational Studies (pp. 1-17). Springer New York.
Rosenbaum, P. R. (2010). Dilemmas and craftsmanship. In Design of Observational Studies (pp. 3-20). Spring er New York.
Safavian, S. R. and D. Landgrebe (1991). "A survey of decision tree classifier methodology." IEEE transactions on systems, man, and cybernetics 21(3): 660-674.
Saunders, M. N. (2011). Research methods for business students, 5/e, Pearson Education India.
Sisheber, B., Fente, D., Adgo, E., & Nyssen, J. (2015). Regional geography of Dek Island, Lake Tana, Ethiopia. In TropiLakes 2015: Tropical lakes in a changing environment: water, land, biology, climate and humans: excursion guide mid-conference excursion (pp. 39-55). Bahir Dar University
Smith, J. A., & Todd, P. E. (2005). Does matching overcome LaLonde's critique of nonexperimental estimators? Journal of Econometrics, 125(1), 305-353.
Zeller, M. (1994). Determinants of credit rationing: A study of informal lenders and formal credit groups in Madagascar. World development, 22(12), 1895-1907.