ORIGINAL ARTICLE

Impact of agricultural credit on maize productivity among smallholder farmers in Hababo Guduru district, Oromia, Ethiopia

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ABSTRACT

Agricultural credit is needed to buy farm inputs such as seed, fertilizer, chemicals, hired non-family farm labor, and to finance farm maintenance costs.In Ethiopia, limited access to agricultural credit facilities is one of the major factors affecting agricultural productivity. We evaluate the impact of credit on maize productivity among smallholder farmers using a cross-sectional survey data from 260 households, 120 who have access to credit and 140 who do not have access to credit, and using propensity score matching method. We find that access to credit increasesmaize productivity by 26.6% via increasing the use of improved maize seed, fertilizer and hired labor, by 37.4%, 47.8% and 33.6%respectively. The result implies that credit enables smallholder farmers to overcome capital constraints and purchase superior quality and high yielding variety seeds, fertilizers and hire labor to enhance agricultural productivity. Policy makers and financial institutions should address constraints of credit and increase credit outreach to enhance agricultural productivity and achieve food security of smallholder farmers.

Key words: Agricultural credit, Maize productivity, Agricultural input, Smallholder farmers, Ethiopia

INTRODUCTION

Maize is one of the world's most widely grown highland cereals and primary staple food crop in many developing countries (Kandil, 2013). Maize ranks third major cereal crop in the world after wheat and rice (Zamir *et al*., 2013). In Ethiopia, maize is grown on more than 2 million ha, which accounts for 15% of the total cultivated land in the country(Gates, 2013). It is second to teff in area coverage but first in productivity and total production among all cerealsgrown in Ethiopia. Approximately 9.3 million smallholder farmers in the country grow maize, mainly for human consumption (Gates, 2013). It is also an important source of income for these farmers.Crop productivity of vastly smallholder dominated Ethiopian agriculture is very low. The national average yield for maize, wheat and sorghum and finger millet was estimated at33.87, 25.35,23.31 and 20.20 t ha^{-1}, respectively (CSA, 2017). The limited use of modern inputs is a major characteristic of crop production and it seems to be a major explanation for its low productivity (Taffesse*et al*., 2011).Low yield per unit area across major crops is common among the Ethiopian smallholder farmers mainly due to limited use of improved inputs.

One of the reasons for limited improved input use is shortage of access to agricultural credit from formal sources. Each credit source has its own conditions that are not often suitable for resource poor smallholder farmersand thus limiting their ability to obtain credit from the formal sources or the amount of credit they wish to borrow. For instance, Owusu-Antwi and Antwi (2010) state that formal financial markets often require collateral in the form of land or houses as a prerequisitefor granting loans to borrowers which are often out of reach of the majority of the farming population. These imply that farmers find it difficult to improve crop productivity without access to credit as it limits their ability to purchase much-needed inputs such as fertilizer, improved seeds, or land for their farming activities.

Improving financial access helps smallholder farmers to improve production and productivity through investment in irrigation, production equipment and inputs, and in postharvest handling, processing and marketing (Amha and Peck, 2010; Simmons and Djurfeldt, 2011). However, in Ethiopia, limited access to credit remains a major challenge for smallholder farmers because of that limited access to production credit to buy and use farm inputs, smallholder farmers cannot afford yield-enhancing inputs; farm productivity often remains low on smallholder farms despite the available technology for achieving higher yields (Onumah and Meijerink, 2012). In the study area, the access of agricultural credit is also not powerful as many factors, which has in turn put another implicationon the agricultural productivity (Hababo Guduru District of Agricultural Office, 2017). Even for some farmers who have access to agricultural credit, whether it improves the crop productivity and livelihood of farmers is not well studied.

Only some studies are conducted in different parts of the countryon the link between access to agricultural credit and agricultural productivity (Shah *et al*., 2008; Saleem and Jan, 2011; Rahaman *et al*., 2014). However, many of these studies are solely based on descriptive analysis or a simple OLS model and did not apply rigorous impact assessment methodologies and are, therefore,subject to serious problems arising from selection bias.Thesestudies fail to establish an adequate counterfactual situation and cannotcontrol for selection biases which arise from unobservable household characteristics.Therefore, in order to assess the impact of access to agricultural credit on maize productivity among smallholder farmers, we aim to assess what the situation would be if the farmers had not participated in credit, i.e., the counterfactual situation.Thus, in this study we use propensity score matching technique to construct a control group of households that have similar probabilities of being selected into credit with those who have access to credit and evaluatethe impact of agricultural credit on maize productivity among smallholder farmers in the study area.

Overview of agricultural credit in Ethiopia

The rural poor over 800 million people in the world require and use a variety of financial services (Gashayie and Singh, 2015). However, inmost cases, these services are inappropriate and provided on usury terms and not on conditions that are conduciveto rural poverty reduction.In addition, financial institutions have demonstrated a lack of interest in financing agriculture (Chalmers et al, 2005).

The rural financial market landscape in Ethiopia is characterized by the coexistence of formal financial services provided bycommercial banks (both public and private), Development Bank of Ethiopia (DBE), credit and saving cooperatives, insurance companies (both public and private) and microfinance institutions (owned by regional governments, NGOs, associations and individuals (NBE, 2014).

Given that most of the smallholder farmers are located in rural areas, have limited networks of financial institutions, they have insufficient access to financial services(EAFF, 2013). Even when there are financial service networks, smallholder farmers have a poor credit rating, especially for medium-term loans. And if they are lucky to qualify for a facility, they get it at such a high interest rate and an unfavorable repayment schedule that can make them bankrupt, pushing them out of farming altogether.

Commercial banks avoid lending to agriculture because agriculture is generally assessed to be a risky sector. In addition, most commercial banks are normally located in the urban areas, making them not readily accessible by the farmers(EAFF, 2013). If banks were to lend to these smallholder farmers, they would also find it costly to extend services to rural areas. Because of the reluctance of commercial banks to meaningfully serve the smallholder farmers, microfinance institutions (MFIs) and rural savings and credit cooperatives (RuSACCOs) have been developed and are evolving to fill this space(Chaka, 2015).

Conceptual Framework

Impact pathway to improved productivity

Figure 1 illustrates the conceptual framework of agricultural credit and crop productivity. During the cropping season resource poor farmers balance their budget when there is high expenditure for input purchase and consumption. With limited access to credit, resource poor farmers' budget for the cropping season can become a constraint on agricultural production.

Given the limitations of credit facilities in rural areas, maize farmers' who have access to creditare expected to increase access and improve their farm input use. The inputs considered in this study include fertilizers, improved seeds and hired labor. Baffoe *et al*. (2014) demonstrate that access to credit enhances agricultural productivity. These results imply that farmers find it difficult to improve productivity without access to credit as it limits their ability to purchase much-needed inputs such as fertilizer, improved seeds, or land for their farming activities. As a result, the productivity of maize farmers is expected to improve. Similarly, Bashir *et al*. (2010) state that extensive and appropriate use of inputs is determined by access to credit. Therefore, there is a potential to improve agricultural productivity through improving access to credit. According to Ashaolu *et al*. (2011), credit allows producers to have access to new inputs and production technologies that can help increase overall agricultural productivity.

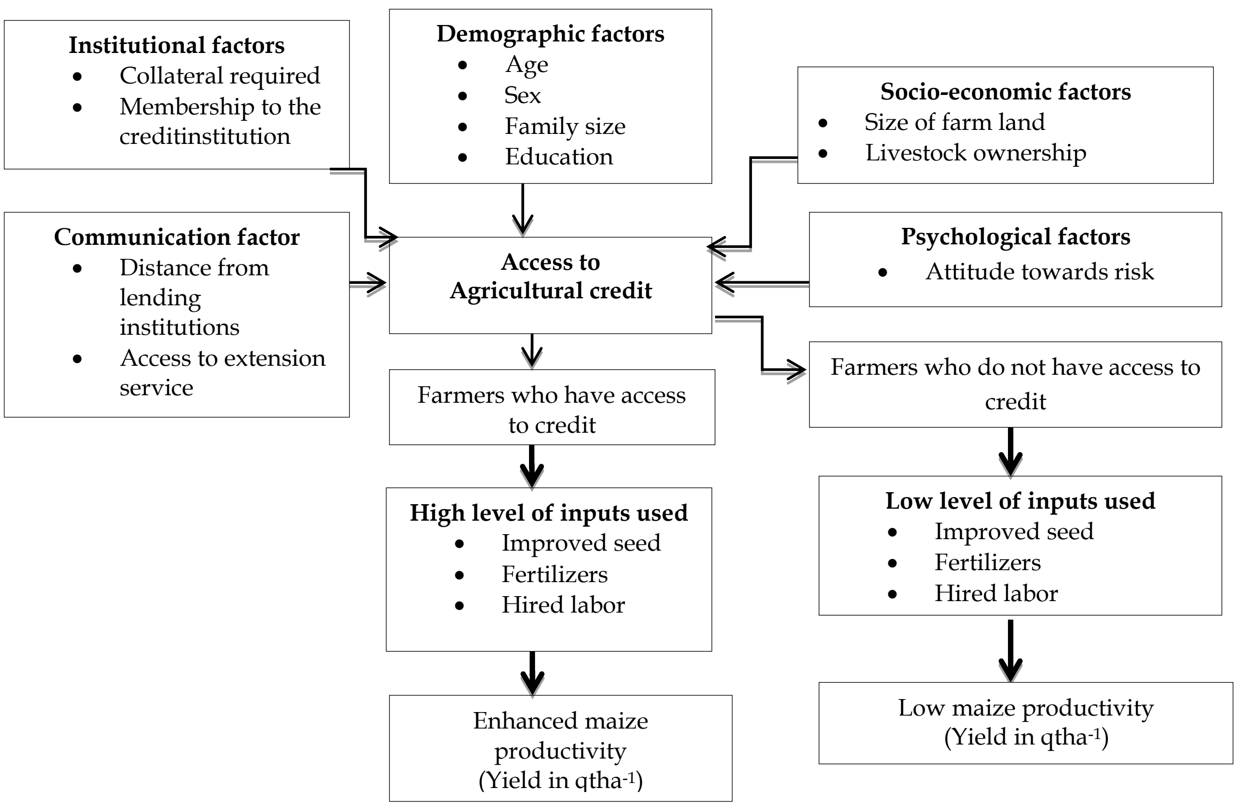

Figure 1: Conceptual framework of the study.Source: Author's construction

RESEARCH METHODOLOGY

Description of the study area

The study was conducted in Hababo Guduru district, which is located in western Oromia, Ethiopia. The district is located at 09º20´N and 37º20´E geographical coordinates and at an altitude of approximately 2296 m.a.s.l. According to the 2011 annual report of the district, the monthly mean temperature varies from 14.9⁰C to 17.5⁰C while the annual rainfall ranges from 1000-2400mm. The area is characterized by favorable climate for maize production including five to six months of rainy season. The study area is classified into different agro climatic zones such as lowland, mid-highland and highland. Mixed crop-livestock farming is the dominant production system in the area.

Sampling procedure

A two stage random sampling procedure was adopted to select sample households.In the first stage, four rural kebeles were selected using simple random sampling method. In the second stage, a total of 260 households, of which, 120 have access to credit (who have takena positive amount of credit) and 140 have no access to credit (who are unable to take any positive amount of credit;they are either member of a credit institution or not), were selected based on probability proportional to size in the respective kebeles. Both primary and secondary data were collected. Primary data were collected from the selected maize producer farmers, and secondary data were collected from office of agriculture, Oromia Credit and Saving Share Company (OCSSCO), Microfinance Institutions (MFIs) and other published and unpublished sources.

Data analysis

To evaluate the impact of access to credit onmaize productivity of smallholder farmers, the following regression model was used:

$$Y_i = \alpha X_i + \beta D_i + \varepsilon_i$$

where Yi measures the potential productivity outcome of a smallholder maize farmer *i*.*Xi*is a vector of explanatory variables, $Di$is treatment variable and $\varepsilon_i$is an error term reflecting unobserved characteristics that alsoaffectsY_i.$\alpha$and$\beta$are parameters to be estimated.The primary objective of this study was to evaluate the impact of access to credit on maize productivity of smallholder farmersand to understand the impact pathwaythrough which maize productivity possibly affected by access to credit.We use the following four outcome indicators: (1) improved maize seed used, measured in kilogram ha^{-1}; (2) amount of fertilizer used for maize production, measured in quintal (qt) ha^{-1}; (3) cost of labor hired for maize production, measured in Ethiopian Birr (ETB) ha^{-1}; (4) maize productivity, measured in qt ha^{-1}.

The impact of credit on maize productivity was evaluated using propensity score matching (PSM) where the observable estimated treatment effects were compared to the counterfactual of control (Rosenbaum and Rubin, 1983). PSM was used as an impact estimator to get unbiased estimates of average treatment effects. The PSM technique enables us to extract from the sample of control households a set of matching households that look like the treated households in all relevant pre intervention characteristics. We estimate the average impact of treatment on the treated (ATT). In this study probit model was used to estimate propensity scores using observed characteristics of the sampled households. In estimating the probit model, the dependent variable was access tocredit, which takes the value of 1 if a household had access to credit and 0 otherwise. Eleven explanatory variablesofdemographic, socio-economic and institutional characteristicswhich are expected toinfluence the access to credit of the i^{th} farmer were used in matching.To provide an organized framework for empirical analysis of the stated hypothesis using PSM variables Y_1 and Y_0 were defined as the potential productivity outcome of randomly assigned smallholder maize producer *i*who has access to credit (Y_1) or has no access to credit (Y_0). The effectiveness of PSM depends on two assumptions: conditional independence (unconfoundedness) and common support.

A$_1$:$Y_1, Y_0 \perp D / X$ unconfoundedness assumption

A$_2$: $0 < P\ (D = 1|Xi) < 1$

Common support assumption

where,Y_0 is the outcome for control households, Y_1 is the outcome for treated households, *D* is the treatment indicator, where *D*= 1 signifies a farmer who has access to creditand 0 otherwise.

We include vector of observable farmer characteristics *Xi*: age, sex, family size,education of household head, land size, livestock ownership (measured in tropical livestock units),distance of farmer's residence from lending institution, collateral required by lenders, extension service, attitude towards risk and years of membership in credit organization.When the matching assumptions are met, the unbiased impact of credit on input use and maize productivity through matching by propensity score can be estimated. The ATE is estimated as the mean difference between outcomes of the treated group, denoted by Y*(1)* and matched control group, denoted by Y*(0)*.The first equation in this subsection represents the model to estimate the ATE.

$$ATE = E[Y\ (1) - Y\ (0)]$$

And also by ATT:

$$ATT = E[Y(1) - Y(0)|D = 1]$$

where, *D* is a dummy for treatment (*D* = 1 for treated, those with access to credit, 0 for control). The mean difference between observables can therefore be written as:

$$E[Y(1)|D = 1] - E[Y(0)|D = 0]$$
$$= ATT + E[Y(0)|D = 1] - E[Y(0)|D = 0]$$
$$= ATT + SB$$

where, SB is selection bias, which is the difference between the counterfactual outcomes for the treated group and the observed outcomes for the control group. If SB is equal to zero then the ATT can be estimated by the difference between the mean observed outcomes for treated and control groups.

Definition of variables and working hypothesis

Table 1: Description, measurement and a priori expectation of the variables used in the probit model and propensity score matching

Variables	Description	Measurement	A priori expectation
Dependent variable			
AACRED	Small holder farmer's access to formal credit	Dummy:1 if access, 0 otherwise	
Outcome variables			
IMSEED	Improved maize seed used	$Kgha^{-1}$	
FERTUSED	Amount of fertilizer for maize	$Qtha^{-1}$	
HLABOR	Labor hired for maize production	ETB	
MAIZEPRO	Maize productivity	$Qtha^{-1}$	
Covariates			
AGEHH	Age of farm household	Years	-
SEXHH	Sex of household head	Dummy:1 if male, 0 otherwise	+
FSIZEAD	Family size in adult equivalent	Number	-
EDULEVEL	Number of years of formal education	Years	-
TOTLHIH	Total land holding in hectare	Hectare	+
TLU	Total livestock unit of farmers	Numbers	-
DISTAINS	Distance institution from farmers home	Km	-
COLLTER	Assets willing to offer to get credit	Dummy: 1 if yes, 0 otherwise	+
FEXTSERV	Frequency of extension contact per a year	Numbers	+
RISK	Risk attitude of the farmers towards credit	Dummy: 1 if yes, 0 otherwise	-
NUYRMEM	Years of membership for formal credit	Number of years	+

Source: Authors computation based on empirical reviews, 2017

For this study, the Nearest Neighbor matching, Caliper matching, Radius and Kernel matching were tested one by one to choose the best estimator for evaluation as well as to avoid bad matches. Finally, Kernel matching estimator with 0.25bandwidth was selected as the best estimator.PSM serves as a balancing method for covariates between the treated and control groups. The idea behind balancing tests is to check whether the propensity score is adequately balanced. In this study, the following methods were used to check the balance of the scores and covariates. First, standardized bias before and after matching were calculated and checked for a significant difference in the covariates of both groups using a two-sample t-test. After matching, there should not be significant differences (Rosenbaum and Rubin, 1983). Secondly,pseudo-R^2 after and before matching were compared and after matching, there should not be systematic differences in the distribution of covariates between both groups;so the lower value of a pseudo R^2 indicates that the balancing property is satisfied (Sianesi, 2004).The conditional independence assumption requires that given observable variables, potential outcomes are independent of treatment assignment (Imbens, 2004). This implies that selection into treatment is based entirely on observable covariates, which is a strong assumption of PSM. Thus, we compute result of sensitivity analysis using Mantel-Haenszel bounds in order to test the robustness of the results against violation of this assumption. In addition to producing valid treatment estimates, we produced valid standard errors with the bootstrap method using 50 replications.

RESULTS AND DISCUSSIONS

Description of sample households' characteristics

Results of analysis of socio-economic characteristicsof the surveyed households are presented in Table 2.The resultsshow that, before matching there were differences between treated and control households in terms of education, land size, total livestock, and years of membership into credit institution, extension contact and distance from credit source.The survey result also shows that the average years of formal education for those who have access to credit was 3.6, while it was 4.45 years for those who have no access.

The mean land sizes for the two categories of farmers are 2.63 and 1.9 respectively for those who have access to credit and for those who do not have access to credit. Farmers who cultivate larger size of land can utilize more capital and also, larger land size reflects ownership of an important asset, which is expected to affect access to agricultural credit. The result revealed that the households that do not have access tocredit owned a larger number of livestock (on average 6.97 TLU) compared to those who have access to agricultural credit (on average 5.64 TLU). This might be an indication that the households that do not have access to credit have financial capital by selling their livestock to purchase input.

Number of year of membership of farmers into formal credit organizations (NUYRMEM) is also the other variable that significantly affects access to formal credit. Average number of years of membership was 6.5 for those who have access to credit and 5.34 for those who do not have access to credit from the formal sources. This has two implications: first,the more years farmers spend in the membership has determining role in getting access to credit. Second, being member into formal credit organization is not sufficient to get credit, i.e. there are other important factors, apart from membership, which affect smallholder farmers' access to credit. Extension contact (FEXTSERV) is also related to smallholder farmers' access to formal credit. An average number of contacts with extension workers were 2.43 per year for those who have access to credit whereas it was only 1.86 for those who do not have access to credit. That is, respondents who had frequent contact with extension agents have more access to credit as compared to those who had no or few contacts.

Results in Table 2also show that the distance the farmers travel to get credit from formal sources affectsfarmers' access to credit. On average, farmers who have access to credit traveled about 1.75 km while their counter parts traveled about 2.69 km to reach the source of credit.

Moreover, the results of categorical variables showed that the proportion of female headed households who have access to credit (7.5%) is lower than the proportion of female headed households in those who do not have access to credit(15%). Larger proportions (51%) of the respondents who do not have access to credit perceive that credit does not have risk than the proportion (46%) of those who have access to credit.

Table 2: Descriptive statistics ofcharacteristics of sample households (for continuous and dummy variables)

Variable	Dummy response	Have access to credit (N=120)		Have no access to credit(N=140)		Total (N=260)		χ2-value
		N	%	N	%	N	%	
Sex	Male	111	92.5	119	85	230	88.5	3.561*
	Female	9	7.5	21	15	30	11.5	
Collateral	Yes	58	48.3	64	45.7	122	46.9	0.178
	No	62	51.7	76	54.3	138	53.2	
Risk attitude	Yes	65	54.2	68	48.6	133	51.2	0.81
	No	55	45.8	72	51.4	127	48.82	

Source: Survey data, 2017. Note: ***, ** and *means significant at 1%and 5% and 10% probability level respectively. SD, CINS: Standard deviation and Credit institutions respectively

Maize productivity and input use

Table 3 summarizes input used for maize production and associated productivity and compares their means between those who have access to credit and those who do not have access to credit using t-test. We observe substantial differences in these variables between farmers that have access to credit and those who do not have access. Those who have access to credit perform better in all outcome indicators. Maize productivity is 30 qtha^{-1} for those who have access to credit and 19 qtha^{-1} for those who do not have access. Farmers who have access to credit produce maize on a larger area of land (0.65 ha); use more improved seed (15.5 kgha^{-1}), fertilizer (1.3 qtha^{-1}), family labor (48.6 person-days), and incur more hired labor cost (114 ETB) than those who do not have access to credit (Table 3).

Table 3: Comparison of means for outcome variables between treated and control farmers

	Have access to credit (N=120)		Have no access to credit (N=140)		Total sample (N=260)		t-value
Variable	Mean	SD	Mean	SD	Mean	SD	
Maize yield(qtha^{-1})	29.56	15.31	19.26	9.63	24.11	12.47	6.0***
Farm size for maize (ha)	0.65	0.24	0.56	0.21	0.6	0.23	3.196***
Improved seed(kgha^{-1})	15.53	5.55	9.69	4.83	12.61	5.19	8.961***
Fertilizer (qtha^{-1})	1.30	0.62	0.78	0.48	1.04	0.55	7.52***
Family labor(person-day)	48.57	11.40	41.0	12.14	44.68	11.77	5.29***
Cost of hired labor (ETB)	114.13	135.14	76.07	144.88	95.1	140.01	2.178**

Source: Authors' calculation from survey data (2017). Note: *** and * means significant at 1% and 10% probability level respectively.

Econometric analysis

Estimation of the propensity scores

The first stage in the propensity score matching is to estimate the probability of having access to credit. The estimated parameters of the probit model result show that credit access status of farm households has been significantly influenced by seven variables (Table 4). The model estimation gave a Pseudo-R^2 of about *0.2504.* The Chi- square statistics show that the model is highly significant at 1%, indicating that the variables included in the model jointly significantly explain the variation in the probability to participate in credit. Age, sex and education of household head, number of livestock holding in tropical livestock unit, extension contact, distance from credit institutions and year of membership in credit institutions affect the probability of getting access tocredit.

The result displayed in Table 4 shows that age of farmers is found to be negatively and significantly associated with the probability of getting access to credit at 10% significance level. It might be due to the fact that older farmers have a larger capital basis not to seek for credit.The result is consistent with the findings of Mpuga (2010) who found that younger farmers more likely borrow, since they are very active and energetic and more aggressive to investment.Being male headed household has positive and statistically significant (at 5%) influence on the probability that households get access to credit.The result is consistent with the findings of Awunyo-Vitor and Abankwah (2012) who documented that males are more likely to get access to credit as compared to their female counterparts. Education level has negative and statistically significant (at 5%) relationship with the probability that a household get access to credit. The negative sign indicates that farmers with more years of formal education are less likely to have access to credit.This result is consistent with results of a study by Feredе*et al.* (2012) who show that educated individuals might be reluctant to take credit and can be risk adverse of market failure.It was also apparent from the results that the number of livestock in tropical livestock unit (TLU) owned by the farmer is found to have a negative and statistically significant (at 1%) influence on the probability that a household gets access to credit. The negative relationship implies that farmers who own more number of livestock less likely seekcredit.The result is supported by the findings of Girma and Abebaw (2015) who found that the larger number of livestock the household owns the less likely the household demand and borrow credit from the formal sources.Frequency of extension services by extension agent (FEXTSERV) has a positive and significant (at 1% probability level) effect on the probability of having access to credit. The result show the important role played by extension agents as sources of information and enforce the farmers to use credit for productive purposes rather than for consumption purposes. Abdalla and Ebiadalla (2012) found that access of farmer to a formal credit institution is positively influenced by participation of the household head in extension activities.Farmers' perception of the distance between credit institutions and his or her house had negative and significant (at 1% probability level) effect on the probability that households get access to credit from formal sources. The result indicates that farmers who perceive the distance between their house and the credit institution to be far are less likely to demand credit from formal sources. This result is consistent with those reported by Tang *et al.* (2010) who found that an extra kilo meter between the nearest bank and village reduces the borrowing probability from the formal lenders by 1%.In addition, the probability of accessing formal credit was also positively and significantly influenced by number of years of membership (NUYRMEM) into formal sources of credit. Abdalla and Ebiadalla (2012) found that access of farmer to formal credit institution is positively influenced by experience of the household head in credit use.

Table 5 provides the estimated propensity scores (PS). PS varies between 0.1295 and 0.9999 (mean = 0.6252) for treated households and between 0.0066 and 0.9756 (mean = 0.3177) for control households. Therefore, our common support region lies between 0.129 and 0.9756. A respondent on common support region means that the observation finds a suitable match, while observations that are off-support fail to find suitable matches. For the treatment and the potential comparison groups 118 and 140 observations were observed to be on-support respectively. Figure 2 portrays the distribution of the households with respect to the estimated propensity scores. In case of treated households, most of them are found in partly the middle and partly in the right side of the distribution. The overlap assumption is said to be satisfied when there is a chance of seeing observations in both the control and the treatment group laid each combination of covariate values for those who have access to credit and those who do not have access to credit. Alternative matching estimators were tried to match the treatment and control groups in the common support region. The final choice of a matching estimator was based on different criteria such as equal mean test, referred to as the balancing test, pseudo- R^2 and matching sample size specifically a matching estimator which balances all explanatory variables (i.e. results in insignificant mean difference between the two groups after matching), bears a lower pseudo-R^2 value, and results in large matched observations is preferable

Table 4: Factors influencing the probability ofgetting access to agricultural credit- results of probitmodel

Variables	Coefficient	Robust Std. Err.	Z	P>|z|	Marginal effects
Age	-0.0174	0.0105	-1.66*	0.097	-0.0069
Sex	0.6845	0.2842	2.41**	0.016	0.2489
Family size (AE)	-0.7307	0. 4720	-1.55	0.122	-0.2889
Education	-0.0749	0.0316	-2.38**	0.017	-0.0296
Land size	0.0889	0.0897	0.98	0.326	0.0348
Livestock holding	-0.1535	0.0416	-3.69***	0.000	-0.0607
Collateral	0.00034	0.1814	0.00	0.999	0.0114
Extension contact	0.3121	0.0952	3.29***	0.001	0.1235
Distance	-0.2237	0.0596	-3.75***	0.000	-0.0885
Years of member-ship for CINS	0.0936	0.0341	2.75***	0.006	0.0370
Risk	-0.1425	0.1795	-0.79	0.427	-0.0564
_cons	0.8194	0.7672	1.07	0.285	

Number of obs=260; Wald chi2 (11) =68.21; Prob>ch2=0.0000; Pseudo R2=0.2504; Log likelihood=134.5169

Source: Authors' calculation from survey data (2017). Note; ***, ** and * is significant at 1%, 5% and 10% level of significance respectively. AE = Adult equivalent

Table 5: Distribution of estimated propensity scores

Group	Obs	Mean	Std. Dev.	Min	Max
All households	260	0.4596	0.2735	0.0066	0.9999
Treatment households	120	0.6252	0.2282	0.1295	0.9999
Control households	140	0.3177	0.2254	0.0066	0.9756

Source: Authors' calculation from survey data (2017)

Accordingly, Kernel Matching with a bandwidth of 0.25 is the best estimator for the data in this study. After choosing the best performing matching algorithm the next task is to check the balancing of propensity score and covariate using different procedures by applying the selected matching estimator. The standardized difference in X before matching was in the range of 5.2% and 64.1% in absolute value whereas after matching, the remaining standardized difference of X for almost all covariates lay between 4.2% and 17.8%. Rosembaum and Rubin (1983) recommend that a standardized difference of greater than 20% should be considered too large and is an indicator that the matching process has failed. As a sufficiently large enough reduction in standardized bias, it is determined that the matching substantially reduced the selection bias. Similarly, *t*-values in Table 7 show that before matching eight of the chosen variables exhibited statistically significant differences while after matching all of the covariates are balanced.The low pseudo-R^2 and the insignificant likelihood ratio tests support the hypothesis that both groups have the same distribution in covariates *X* after matching (Table 8). These results clearly show that the matching procedure is able to balance the covariates in the treated and the matched comparison groups.

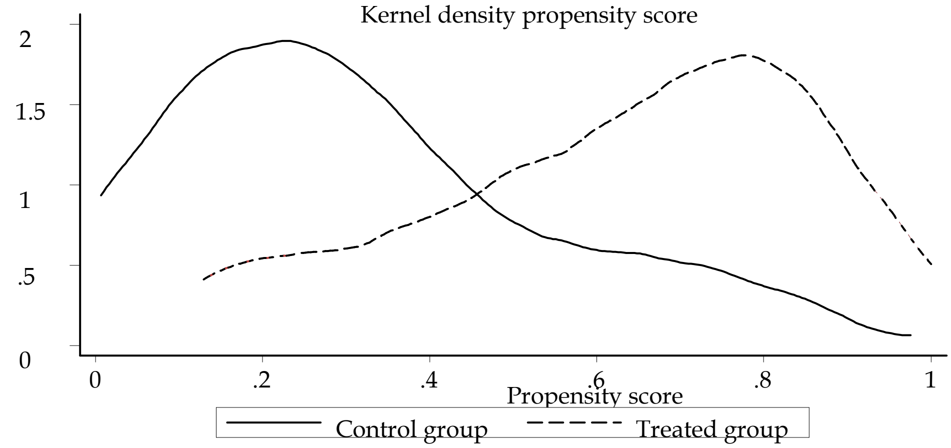

Figure 2: Propensity score distribution for treated and control groups. Source: Authors' calculated value from survey data (2017).

Average treatment effect on the treated

Table 9 presents the results of the mean treatment effect on the treated (ATT). The estimated results indicate that access to credit increases maize productivity by 9.39 - 11.62 qtha^{-1}, the use of improved seed by 5.25 - 5.80 kg ha^{-1}, fertilizer by 0.52 -0.57 qtha^{-1}, costs incurred for hired labor by 5.46 - 37 ETB. This implies that access to credit increases maize productivity, the use of improved seed, fertilizer, and costs incur for hired labor by about 26.6%, 37.4%, 47.8%, and 33.6% respectively. The result is in line with Appiah*et al*. (2016) who argue that credit largely and positively influences the acquisition of agricultural inputs like improved seed, fertilizers and hired labor. Moreover, Owusu-Antwi and Antwi (2010), Ashaolu*et al*. (2011) and Rahman*et al*. (2014) emphasize agricultural credit as a major determinant of farm productivity.

In order to check for unobservable bias, sensitivity analysis was performed on the computed outcome variables using Rosenbaum Bounding (1983) approach. The first column of Table 9below shows those outcome variables which bear statistical difference between treated and control groups in our impact estimates. The rest of the values which correspond to each row of the significant outcome variables are p-critical values (or the upper bound of Wilcoxon significance level Sig+) at different critical value of e^{γ}**.** Results show that the inference for the effect of access to agricultural credit on the input use and maize productivity of farm households is not changing though the treated and control households have been allowed to differ in their odds of being treated by up to 200% (e^{γ}= 3**)** in terms of unobserved covariates. Thus, it is possible to conclude that our impact estimates (ATT) are insensitive to unobserved selection bias, pure effects of the access to agricultural credit.

Table 6: Performance of matching estimators

Matching Estimator	Performance Criteria		
	Balancing test*	Pseudo-R2	Matched sample size
Nearest Neighbor Matching			
NN(1)	10	0.037	253
NN(2)	10	0.037	253
NN(3)	10	0.035	258
NN(4)	10	0.034	258
NN(5)	10	0.029	258
Caliper Matching			
Caliper (0.01)	10	0.037	253
Caliper (0.1)	8	0.144	258
Caliper (0.25)	8	0.144	258
Caliper (0.5)	8	0.144	258
Radius Matching			
Band width of (0.01)	4	0.249	258
Band width of (0.1)	4	0.249	258
Band width of (0.25)	4	0.249	258
Band width of (0.5)	4	0.249	258
Kernel Matching			
Kernel bw (0.01)	10	0.125	224
Kernel bw (0.1)	10	0.026	258
Kernel bw (0.25)	11	0.021	258
Kernel bw (0.5)	8	0.067	258

Source: Authors' calculation from survey data (2017). Note: * indicates number of explanatory variables with no statistically significant mean differences between the matched groups of treated and control households.NN,bw: Nearest Neighbor and bandwidth respectively.

CONCLUSION AND POLICY IMPLICATIONS

This paper analyzed the effects of agricultural credit on maize productivity among smallholder farmers in Horro Guduru Wollega Zone, Ethiopia. Using data from 260 randomly selected sample households, consisting of 120 who have access to credit and 140 who donot have access to credit from formal sources, and using propensity score matching, we find substantial effects of access to agricultural credit on maize productivity. The main effect pathways are through enhancing farmers' ability to acquire and use agricultural inputs such as improved seed, fertilizer and hired labor.The results imply that agricultural credit has a potential to help enhance the agricultural productivity of the farmers in the study area. If the smallholder farmers get access to credit services which help them to acquire quality agricultural inputs timely, they will undoubtedly end with a better agricultural productivity which will create better income and increase their food security.

In the study area, MFIs and OCSSCO are the major sources of agricultural credit. Therefore, improving the capacity of these institutions must be at the front sight of the government's rural finance policy agenda and creating enabling environment for increased credit outreach. The government must work in creating new strategic linkages between banks, microfinance institutions and OCSSCO and strategies to increase loanable capital. This may create opportunities to share the experiences of MFIs and OCSSCO on how to deliver financial services in rural areas and the financial resources of banks.

Table 7: Propensity score and covariates balancing

		Mean		Standard bias		T-test	
Variable	Sample	Treated	Control	Bias%	(%)Reduc	t-value	P>ltl
_pscore	U	0.606	0.331	125.7		10.09	0.000
	M	0.599	0.553	21.3	83.0	1.69	0.093
Age	U	42.542	43.014	-5.2		-0.42	0.677
	M	42.720	43.723	-11	-112.2	-0.86	0.391
Sex	U	0.925	0.850	23.8		1.89*	0.060
	M	0.924	0.946	-7	70.4	-0.69	0.492
Family size	U	0.616	0.574	20.5		-1.66*	0.099
	M	0.618	0.619	-0.1	99.5	-0.01	0.994
Education	U	3.601	4.436	-27.8		-2.22**	0.027
	M	3.661	3.972	-10.4	62.7	-0.84	0.405
Land size	U	2.630	1.934	40		3.16***	0.002
	M	2.609	2.461	8.5	78.7	0.45	0.651
Livestock	U	5.645	6.976	-57		-4.56***	0.000
	M	5.658	5.756	-4.2	92.6	-0.38	0.704
Collateral	U	1.517	1.543	-5.2		-0.42	0.675
	M	1.525	1.563	-7.4	-42	-0.57	0.568
Extension	U	2.433	1.864	47.9		3.92***	0.000
	M	2.339	2.227	9.4	80.4	0.82	0.416
Distance	U	1.751	2.693	-64.1		-5.09***	0.000
	M	1.770	1.897	-8.6	86.5	-0.79	0.429
Membership	U	6.500	5.343	46		3.72***	0.000
	M	6.381	6.174	8.30	82	0.65	0.516
Risk	U	1.458	1.514	-11.2		-0.9	0.370
	M	1.458	1.368	17.8	-59.6	1.39	0.165

Source: Authors' calculation from household survey, 2017. Note: ***, ** and * indicate the level of significance at 1%, 5% and 10% respectively.U = before unmatched, M = after matching.

Table 8: Chi-square test for the joint significance of variables

Sample	Pseudo R2	LR chi2	p>chi2
Unmatched	0.250	89.86	0.00
Matched	0.021	6.72	0.876

Source: Authors' calculation from survey data (2017)

Table 9: Estimates of the average treatment effect on treated for maize productivity and input (ATT)

Outcome variable	Matching algorithm	Treated	Controls	ATT	S.E[a]	T-value
	Nearest neighbor matching	43.76	32.14	11.62	1.92	6.06***
Maize	Caliper Matching	43.76	32.14	11.62	1.92	6.06***
productivity	Radius caliper matching	43.681	34.295	9.39	1.065	8.81***
(qtha^{-1})	Kernel-based matching	43.68	32.45	11.23	1.68	6.68***
	Nearest neighbor	15.54	10.51	5.80	0.99	5.03***
Amount of improved	Caliper Matching	15.50	10.31	5.25	1.25	4.16***
seed used (kg ha^{-1})	Radius Matching	15.52	9.78	5.80	0.56	10.43***
	Kernel-based Matching	15.50	10.36	5.25	0.83	6.17***
	Nearest neighbor	1.29	0.75	0.56	0.09	5.69***
Amount of fertilizer	Caliper Matching	1.29	0.68	0.62	0.09	6.65***
used (qt ha^{-1})	Radius Matching	1.29	0.78	0.52	0.06	8.51***
	Kernel-based Matching	1.29	0.73	0.57	0.09	6.52***
Hired labor	Nearest neighbor	113.78	108.32	5.46	25.84	0.21
used (Birr)	Caliper Matching	113.78	108.32	5.46	25.84	0.21
	Radius Matching	113.53	76.07	37.45	14.04	2.67**
	Kernel-based Matching	113.53	94.18	19.35	19.79	0.98

Source: Authors' calculation from survey data (2017)

Note: *** and**, denote statistical significance at the 1% and 5% level of significancerespectively.[a]Boot strapped standard error with 50 replications.

Table 10: Mantel-Haenszel (1959) Bounds for maize productivity

Outcome variables	e^{r}=1	e^{r}=1.25	e^{r}=1.5	1.75	e^{γ}= 2	e^{γ}= 2.25	e^{γ}= 2.5	e^{γ} = 2.75	e^{γ} = 3
MAIZSEED	0.000	0.000	0.000	0.000	2.1E-07	3.4 E-06	1.6 E-05	1.4 E-04	1.2 E-04
TAFERTM	0.000	0.000	0.000	0.000	5.2E-08	6.2E-07	7.5E-06	9.3E-05	11.2E-04
TLPMAIP	0.000	0.000	0.000	0.000	4.1 E-010	3.4 E-09	1.8 E-08	1.5 E-07	3.2 E-06
MAIZEPRO	0.000	0.000	0.000	0.000	6.5 E-07	3.6E-05	4.7 E-04	7.2 E-03	5.4 E-03

Source: Authors' calculation from survey data (2017)

e^{γ}(Gamma) = log odds of differential due to unobserved factors where Wilcoxon significance level for each significant outcome variable is calculated.Note: MAIZSEED,TPLMAIP, QUAFERTM, MAIZEPRO: Maize seed used, Total paid labor used for maize production, Total amount of fertilizer used for maize production andMaize productivity respectively.

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