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Impact of Improved Soybean (Belessa-95) Variety on Income among Smallholder Farmers in Bambasi Woreda, Benishangul Gumuz Regional State

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ABSTRACT

The importance of agricultural technology in enhancing the welfares of farmers can be realized when yield gain from the technologies results in meaningful income gain. This article aimed to assess economic impact of improved soybean (Bellessa-95) variety on income among farm households in Bambasi District, BGRS. In this study a multi-stage stratified sampling technique was employed to select rural kebeles and households. Three rural kebeles were selected randomly. Structured interview schedule was developed, pre-tested and used for collecting the essential quantitative data for the study from 134 randomly selected households. Descriptive statistics and propensity score machining (PSM) models were employed to analyze data. Results of descriptive analysis showed that there were statistically significant differences between adopter and non-adopter households with distance to market, livestock ownership, and frequency of extension visit, farm income as well as number of oxen owned. Consistent with the findings of previous studies, regression results showed that adoption of improved soybean has a positive and significant effect on farm income by which adopters are better-off than non-adopters. Based on results obtained it is recommended to continuous training in improved soybean production. Promoting farmers to form or join cooperatives. Strengthening demonstration centers and Farmers Training Centers (FTC). Transaction costs should be reduced and scaling up and diffusion of improved soybean varieties in the study area should be broadened.

1. INTRODUCTION

1.1. Background of the study

In Ethiopia, agriculture takes the lion's share (72.7%) in terms of employment. The sector is the livelihood of the 75.26 million (79.77%) of the population. It is the source of food and cash for those who are engaged in the sector and others. Most agricultural holders acquire the food they consume and the cash they need to cover other expenses only from farming activities. Since farming in Ethiopia is often precarious and usually at the mercy of nature, it is invariably an arduous struggle for the holders to make ends meet (UNDP, 2014).

The last five-year Growth and Transformation Plan (GTP) (2010/11-2014/15) and the second GTP (2015/16-2020/21) gives special emphasis to the role of agriculture as a major source of economic development. Following the Agricultural Development-Led Industrialization (ADLI) strategy and building on PASDEP achievements, the GTP has the priority to intensify productivity of smallholders and strongly supports the intensification of market-oriented agriculture, either at national or international level, and promotes private investments. The plan includes scaling up of best practices to bring average farmers' productivity closer to those of best farmers, expanding irrigation coverage and shifting to production of high value crops to improve income of farmers and pastoralists, with complementary investments in market and infrastructure development (FAO, 2012).

Soybean is among the cash crops which have been given priority in the national effort of meeting increased income and nutritional security of households. To this effect number of improved soybean varieties have been developed by the national research system and disseminated among smallholder farmers. Benishangul Gumuz region is one of the beneficiary regions of the country since 2006. The region has 156,000 ha of land that is suitable for soybean production. However, the contribution of the already disseminated varieties has not been well understood among the beneficiary farmers for informed decision making and to justify further expansion of soybean production zone in the region.

Kathelen (2010) reported on his study that a well-designed impact assessment study can provide insight in to the causal factors behind the success and failure of various improved variety adoption activities. Impact assessment thus provides information that allows research and extension institutions to improve their services, and improve the welfare of the farmer. Moreover, ADB (2006) indicated that project impact evaluation established whether the intervention had a welfare effect on individuals, households, and communities, and whether this can be attributed to the concerned intervention.

Generally, the focus of impact assessment goes beyond the products of research (such as improved variety) to determine the effects of adoption of its products. In other words, adoption of the products of research is a prerequisite for attaining impact. Impact assessment is done for several reasons including accountability, improving future design, prioritizing and implementation of similar programs. As FAO (2000) put it; the results of this process provide continuous feedbacks to the project planning, prioritizing and implementation. It can be undertaken before initiating the project (ex-ante), during the project period (midterm) or after the completion (ex-post) of the project or activity (Anandajayasekeram*, et al.,* 1996).

1.2. Statement of the Problem

Though traditional agriculture prevails in developing countries in general and in Ethiopia in particular, some progress has been made in using improved agricultural technologies and inputs. High yielding soybean varieties are among important technologies promoted by the country's agricultural research and extension system.

A good technology has to guarantee sustainable productivity across niche agro ecologies and over a period of time. The possible outcomes of a research undertaking are commonly conceptualized in terms of yield increases or reducing yield losses. However, such yield increases often require additional inputs, which lower the effective value of yield gains. Farmers particularly resource poor ones, will only adopt technologies if net yield gains are significantly greater than zero. (Mills, 1997 cited by Mengistu, 2003).It is then very important to know whether additional yields or returns obtained as a result of using an improved technology are sufficient enough to qualify technology for wide scale dissemination. In this respect, technical changes brought about research have to be evaluated for the benefit that the farmers get from them.

Added to this, in developing countries like Ethiopia, some new agricultural technologies have been only partially successful in improving productive efficiency. One of the probable reasons might be farmers' deviation in the use of associated inputs from the developed technological packages. Farmers may not be able to operate at higher levels of inputs because of capital scarcity or lack of access to purchased inputs. Consequently, analysis of the impact of new varieties should begin with how the characteristics of the variety and characteristics specific to small farmers interact. More precisely, increasing production and ultimately the income levels of smallholder farmers through technological advancement requires better understanding of the production system and producers' behavior in the use of farm resources.

The adoption of improved technologies that enhance agricultural productivity and improve annual income of smallholder farmers in Benishangul Gumuz

Region is instrumental for achieving better economic growth of the farmers. Dissemination of improved soybean variety known as *Bellesa-95* was started in 2006 with few early adopters in the region especially in Bambasi *woreda* in order to increase crop productivity and incomes for small scale farm household. However, its impact on farm income were not known and no effort had been made to evaluate the program and its activities hence creating an information gap that needed to be filed. In spite of the government's efforts to address the issue of low productivity, scaling up and dissemination of improved varieties are in progress such as improved soybean varieties. But the impact of the improved soybean on income is not studied in the study area. Therefore; this study was intended to assess the impact of improved soybean *(Bellesa-95)* on household income.

1.3. Significance of the Study

A comprehensive understanding of impact of improved varieties in a diverse environment is necessary to design appropriate strategies to harness their potential benefits in target domains. Research and extension workers engaged in development and transfer of production technologies can utilize the results of this study in setting research and extension agenda. The assessment is important to better inform policy makers about the contribution of soybean varieties. It helps draw good lessons about the performance of existing approaches to development and poverty reduction thus improves targeting of research programs. Smallholder soybean farmers also benefit to foster adoption and diffusion of new agricultural technologies. Other similar studies elsewhere will also benefit by using the information generated by this study.

1.4. Scope and Limitation of the Study

The study covers only Bambasi *Woreda* of Benishangul Gumuz region. This is mainly because of the limited resource available and time to undertake the study on a wider scale. The study impact of improved soybean (*Bellesa-95*) variety on the farm income of smallholder farmers. The study was based on cross sectional data and single variety and may not show the dynamics of impact from soybean technology adoption.

1.5. Objectives of the study

The general objective of the study is to analyze impact on income of improved soybean (*bellessa-95*) variety among farm households.

Specific objectives include

1. To assess socio-economic factors that affect use of improved soybean varieties.
2. To analyze the impact of soybean adoption on farm income of farmers in the study area.

2. RESEARCH METHODOLOGY

2.1. Description of the Study Area

Assosa zone is located 664 km southwest of Addis Ababa. Based on CSA (2013), this Zone has a total population of 310,822, of whom 158,932 are men and 151,890 women. When we see number of urban inhabitants it is 39,957 or 12.86% of the population in the *woreda*. A total of 72,879 households were counted in this Zone.

Bambasi *woreda* is located 629 km southwest of Addis Ababa and about 45 km southeast of Assosa, the capital city of Benishangul Gumuz Regional State (BGRS). The *woreda* is geographically located at 9°45′N latitude and 34°44′E longitude (Figure 3). It is one of the 20 *woredas* in the Benishangul-Gumuz Region of Ethiopia. Part of the Assosa Zone, it is bordered by the Mao-Komo special *woreda* on the southwest, Asossa in the northwest, Oda Buldigilu in the northeast, and by the Oromia Region in the southeast. The *Woreda* has an area of about 784.4 square kilometers.

According to CSA (2015) total population for this *woreda* is 71,279 out of this 37543 (52.65%) are male and 33,736 (47.34%) are female. The altitude of the area ranges from 1300-1470 m.a.s.l. The temperature of the area ranges from 21-35^{o}C. The rainfall of the area has unimodal pattern extending from May to October with and annual mean of 1350 to 1450 mm.

In the *woreda* the common crops grown are maize, sorghum *Teff*, chickpea and groundnut. The study area is also suitable for oil crops like soybean and noug. In addition to this, perennial crops such as mango and avocado are common in the *woreda.*

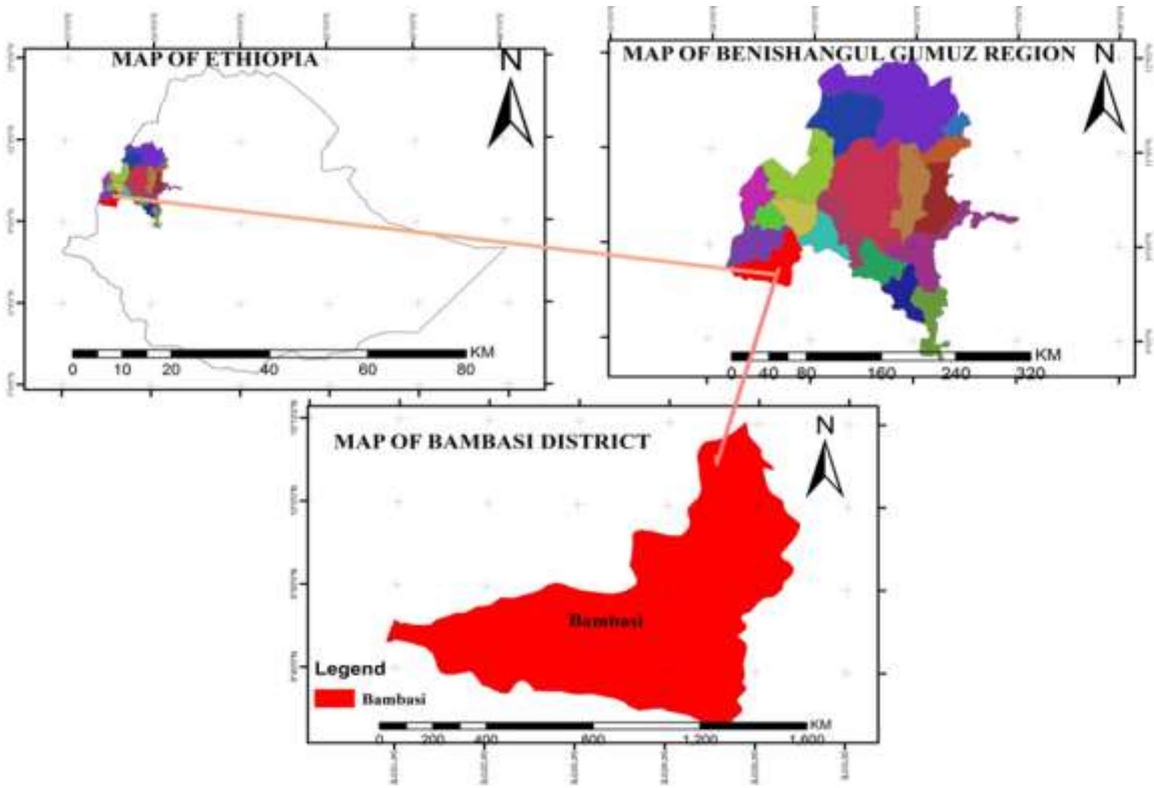

Figure 1. Map of Study Area
Source: Own sketch (2017)

2.2. Sampling Technique and sample size

A clear and precise identification and definition of the population of the study is an important prerequisite for research sample design. In this study, a three stage sampling procedure was adopted to collect the required primary data. In the first stage, among the seven districts in Assosa Zone, Bambasi woreda was selected purposively since scaling-up of improved soybean variety (Bellesa-95) was implemented in the district. In the second stage among 26 kebeles in the woreda three of them (Dabus, Amba-16 and mender-46) were randomly selected. Finally, stratified random sampling method was employed to identify sample households for inclusion in the study. To this effect, list of adopter households was obtained from district agricultural office and from development agents at each sample kebeles and then households in the area were categorized into 2 strata, that is 483 adopter of improved soybean households, and 612 non-adopter households. The total sample was determined using Cochran (1977) stratified sampling procedure considering resource limitation of the study for the Woreda. The sample size thus obtained was assigned to each kebele based on probability proportional to size of the households. 134 sample respondents, 67 sample households from each category were drawn randomly based on probability proportional to sample size (PPS). These both groups were chosen based on their close similarity in their socio-economic characteristics.

$$n_0 = \frac{z^2 pq}{e^2} \qquad 1$$

Where, n_0 is the sample size, Z is the selected critical value of desired confidence level (1.96), p is the estimated proportion of an attribute that is present in the population. q =1-p and e is the desired level of precision which is 0.08.

Table 1: Soybean producers selected from each identified kebeles

Name of the kebeles	Adopter households		Non-adopter households		Total Sample households selected
	Total	Sample	Total	Sample	Total sample
Dabus	123	17	202	22	39
Amba-16	210	29	240	26	55
Mender-46	150	21	170	19	40
Total	483	67	612	67	**134**

2.3. Type and Methods of Data Collection

Primary and secondary data were collected through semi-structured schedule and checklists respectively. Trained enumerators were used to collect the data. Primary data was collected from sample households and secondary data sources were woreda administration and some published documents.

The type of primary data collected include households' demographic characteristics, asset endowments, access to market, access to credit, membership in different rural institutions, and income sources. Interviews were conducted with district level agricultural experts on production and productivity of improved soybean to generate supplementary (qualitative) data. In addition, Focus Group Discussions (FGD) was conducted with groups of selected farmers from each sample kebeles to support interpretation of results obtained from field survey on changes in adoption of improved soybean technologies and their impact on household income

2.4. Method of Data Analysis

2.4.1. Descriptive and inferential statistics

Descriptive statistics such as mean, standard deviation, percentages, frequency, charts, and graphs, used to describe different categories of sample units with respect to the desired socioeconomic characteristics. Moreover, inferential statistics such as chi-square test (for categorical variables) and t-test (for continuous variables) were used to compare and contrast different categories of sample units with respect to the desired characters so as to draw some important conclusions.

Econometric analysis

Propensity score matching method

There are three potential source of bias in impact studies. The first one is that participant households may significantly differ from non-participants in a community as well as household level due to observable characteristics (such as geographic remoteness, or a household's physical and human capital stock) that may have a direct effect on outcome of interest. Secondly, the difference arises due to unobservable community level characteristic. For instance, dynamic leaders at community level may in part drive the existence of a project. At the household level, some households may have certain advantages such as good entrepreneurial spirit or relationship with other programs/projects that may significantly influence behavior. Thirdly, externalities (spillover effect) exerted by project on non-participants (Davis *et al*., 2010). Because of the above problems, differences between participants and non-participants may, either totally or partially, reflect initial differences between the two groups rather than the effects of participating in the scaling out program.

The use of PSM to minimize selectivity bias thus suggests that these differences are the result of participating in scaling up/out program rather than the intrinsic characteristics of the sampled households. However, like the simple mean comparison, PSM may misinterpret the treatment effect, because it only controls for observed variables, and hidden self-selectivity bias may remain. PSM is chosen for this study because it does not require baseline data, the treatment assignment is not random and considered as second-best alternative to experimental design in minimizing selection biases mentioned above (Baker, 2000).

Moreover, assuming that technology adoption is a function of a wide range of observable characteristics at household level, removing the assumption of ‘‘constant technology effect’’ allows us to follow the PSM method (Mendola, 2007).

Rosenbaum and Rubin (1983) were the first to develop the PSM statistical tool. The technique has attracted attention of social program evaluators (Jalan and Ravallion, 2003; Dehejia and Wahba, 1999). PSM is a non-parametric estimation method that works by re-weighting the comparison sample to provide an estimate of the counterfactual of interest what the outcome of a beneficiary household would have been had it not received program benefits. Since dissemination of improved soybean variety is targeted small holder farmer's comparison of mean outcomes between beneficiaries and non-beneficiaries would lead to bias estimates. In order to solve this problem the study used the matching technique called propensity score matching method, which is capable of extracting comparable pair of treatment comparison households in a non-random program setup and absence of base line data.

Specification of the PSM method

According to Caliendo and Kopeinig (2008), the estimation of the impact of household's adoption of improved soybean on a given farm income (Y) is specified as:

$$\tau_i = Y_i(D_i = 1) - Y_i(D_i = 0) \qquad 2$$

Where τ_i is treatment effect (effect due adoption of improved soybean), Yi is farm income of household *i*, Di is whether household *i* has got the treatment or not (i.e., whether a household is adopt or not).

However, one should notice that) *Yi* (*Di* = 1) and Yi (*Di* =0) cannot be observed for the same household at the same time. Depending on the position of the household in the treatment (adoption of improved soybean), either *Yi* (*Di* =1) or *Yi* (*Di* =0) is unobserved outcome (called counterfactual outcome). Due to this fact, estimating individual treatment effect τ_i is not possible and one has to shift to estimating the average treatment effects of the population than the individual one. Most commonly used average treatment effect estimation is the 'average treatment effect on the treated (τ_{ATT}), and specified as:

$$\tau_{ATT} = E(\tau/D = 1) = E[Y(1)/D = 1] - E[Y(0)/D = 1] \quad (3)$$

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 is not a good idea especially in non-experimental studies, since it is likely that components which determine the treatment decision also determine the outcome variable of interest.

In this particular case, variables that determine household's decision to adopt improved soybean could also affect household's farm income. Therefore, the outcomes of individuals from treatment and comparison 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 (2), one can get the following specification for ATT.

$$E[Y(1)/D = 1] - E[Y(0)/D = 0] = 0 \quad (4)$$

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. i.e., when there is no self-selection bias. This condition can be ensured only in social experiments where treatments are assigned to units randomly (i.e., when there is no self-selection bias). In non-experimental studies one has to introduce some identifying assumptions to solve the selection problem. The following are two strong assumptions to solve the selection problem.

i. Conditional Independence Assumption (CIA)

The Conditional Independence Assumption is given by:

$$\mathrm{Y}(0), \mathrm{Y}(1) \coprod D/X, \forall X \quad (5)$$

Where: C indicates independence, X -is a set of observable characteristics,

Y (0) is non-adopter, and Y (1) is adopter.

Independence indicates that given a set of observable covariates (X) which are not affected by treatment (in our case, adoption of improved soybean) and potential outcomes (farm income) are independent of treatment assignment (independent of how adoption decision is made by the household).

This assumption implies that the selection is solely based on observable characteristics (X) and variables that influence treatment assignment (households' adoption decision) and potential outcomes (farm income) are simultaneously observed (Bryson *et al*. 2002; Caliendo and Kopeinig, 2008). Hence, after adjusting for observable differences, the mean of the potential outcome is the same for D = 1 and D =0 and $E(Y_0/D = 0, X)$

Instead of conditioning on *X*, Rosenbaum and Rubin (1983), suggest conditioning on a propensity score (propensity score matching). The propensity score is defined as the probability of participation for household *i* given a set *X* which is household's characteristics, $P(X) = pr(D = 1/X)$. Propensity scores are derived from discrete choice models, and are then used to construct the comparison groups. Matching the probability of participation, given covariates solves the problem of selection bias using PSM (Liebenehm *et al.,* 2009). The distribution of observables *X* is the same for both participants and nonparticipants given that the propensity score is balancing score (Liebenehm *et al.,* 2009).

Matching can be performed conditioning on P(X) alone rather than on X, where P(X) = Prob (D=1|X) is the probability of adoption of improved soybean conditional on X. If the outcomes without the adoption are independent of participation given X, then they are also independent of participation given P(X). This reduces a multidimensional matching problem to a single dimensional problem. Due to this, differences between the two groups are reduced to only the attribute of treatment assignment, and unbiased impact estimate can be produced (Rosenbaum and Rubin, 1983).

ii. Common support region assumption

Imposing a common support condition ensures that any combination of characteristics observed in the treatment group can also be observed among the control group (Bryson *et.al*. 2002). The common support region is the area which contains the minimum and maximum propensity scores of treatment and control group households, respectively. It requires deleting of all observations whose propensity scores is smaller than the minimum and larger than the maximum of treatment and control, respectively (Caliendo and Kopeinig, 2008). This assumption rules out perfect predictability of D given X.

That is $0 < P(D = 1/X) < 1 \quad (6)$

This assumption improves the quality of the matches as it excludes the tails of the distribution of *P(X)*, though this is done at the cost that sample may be considerably reduced. Yet, non-parametric matching methods can only be meaningfully applied over regions of overlapping support. No matches can be formed to estimate the parameters when there is no overlap between the treatment and comparison groups. This assumption ensures that persons with the same X values have a positive probability of being both participants and non-participants.

Given the above two assumptions, the PSM estimator of ATT can write as:

$$\tau_{ATT} = E[Y_1 - Y_0/D = 0, P(X)] = E[Y_1/D = 1, P(X)] - E[Y_0/D = 0, P(X)] \quad (7)$$

Where p(X) is the propensity score computed on the covariates X. Equation (10) shows that the PSM estimator is the mean difference in outcomes over the common support, appropriately weighted by the propensity score distribution of participants.

According to Caliendo and Kopeinig (2008), there are steps in implementing PSM. These are estimation of the propensity scores, choosing a matching algorithm, checking on common support condition testing the matching quality and sensitivity analysis if it is necessary.

3.1.1.1.1. Estimation of the propensity scores

Propensity score involves a series of empirical steps. First, logit model that predicts the probability of each household adopting improved soybean (propensity score) as a function of observed household and community characteristics was estimated, using a sample of adopters and non-adopters. In estimating the propensity score, the dependent variable used in the model was a binary variable a value of 1 for adopters of improved soybean variety and 0 otherwise.

The estimates of individual adoption using logit model are useful for two reasons. First, it gives some insight regarding the observable variable that should be included in the balancing function. Second, it provides a better understanding of adoption of improved soybean variety by the *kebeles* people.

According to Gujrat (2004), the logistic distribution function for the determining factors for adoption of improved soybean of the household can be specified as:-

$$\mathrm{p(i)} = \frac{1}{1+e^{-zi}} \quad (8)$$

Where p(i) is a probability of a household being diversified for i^{th} household and Z(i) is a function of m explanatory variables (Xi) and expressed as:

$$Z(i) = \beta_o + \beta_1 X_1 + \beta_2 X_2 + \cdots \beta_m X_m \quad (9)$$

Where β_0 is the intercept and β_i is the slopes parameter in the intercept in the model which is estimated using maximum likelihood method.

The probability that a household belongs to not adopt is:

$$(1 - \mathrm{Pi}) = \frac{1}{1+\mathrm{e}^{\mathrm{z(i)}}} \quad (10)$$

Therefore,

$$\left(\frac{P_i}{1-p_i}\right) = \frac{1+e^{z(i)}}{1+e^{-z(i)}} = e^{z(i)} \quad (11)$$

And

$$\frac{P_{(i)}}{1-p_{(i)}} = \frac{1+e^{z(i)}}{1+e^{-z(i)}} = e^{\beta_o} + \sum_{i-1}^{m} \beta_i \, Y_i \quad (12)$$

Taking the natural logarithms of the odds ratio of equation (15) will result in what is known as the logit model as included below:

$$ln\left(\frac{P_{(i)}}{1-p_{(i)}}\right) = \ln\left[e^{\beta_o} + \sum_{i=1}^{m} \beta_i \, x_i\right] = Z_{(i)} \quad (13)$$

If the disturbance term U_i is taken in to account the logit model becomes:

$$Z_{I} = \beta_O + \sum \beta_i \, X_i + U_i \quad (14)$$

3.1.1.1.2. Choice of matching algorithm

After estimation of the propensity score, seeking an appropriate matching estimator is the major task of program evaluator. There are different matching estimators in theory. However the most commonly applied matching estimators are Nearest Neighbor matching (NN) Caliper matching, Kernel and local linear matching (Smith and Todd, 2005). The performance of different matching algorithms varies case-by-case and depends largely on the data sample (Caliendo and Kopeing, 2008).

Nearest-Neighbor Matching: In NNM, an individual from a comparison group is chosen as a matching partner for a treated individual that is closest in terms of propensity score Caliendo and Koping, (2008). For each control unit this method assigns a weight equal to one for the nearest comparison unit in terms of the balancing score and zero to all the other comparison observations. NN matching can be with replacement, and without replacement. In the case of matching with replacement a single comparison unit can be used as a match for more than one treatment unit. On the other hand, NN matching without replacement, a comparison individual can be used only once and increases bias but it could improve the precision of the estimates (Abadie and Imbens, 2006).

Kernel Matching: This is another matching method whereby all treated units are matched units with a weighted average of all controls with weights which are inversely proportional to the distance between the propensity score of treated and controls (Becker and Ichino, 2002). The weighting function is a (Gaussian) kernel density. All the observations in the comparison group inside the common support region are used, the farther the comparison unit from the control unit the lower the weight. The kernel estimator matches treatment units to a kernel a weighted average of comparison units. This can be thought as a non-parametric regression of the outcome on a constant term. For the treatment units, weights are given by:

$$W(i,j) = G\,\frac{Pj-Pi/hn)}{\sum KI_o G\left(\frac{P_k-P_i}{hn}\right)} \qquad (15)$$

Where G (i,j) is a kernel function and h_n is a bandwidth parameter.

Radius matching method: is each treated unit is matched only with the control units whose propensity score falls in a predefined neighborhood of the propensity score of the treated unit. If the dimension of the neighborhood (i.e. the radius) is set to be very small it is possible that some treated units are not matched because the neighborhood does not contain control units. On the other hand, the smaller the size of the neighborhood the better is the quality of the matches.

Caliper Matching: With radius matching each treated unit is matched only with the untreated units whose propensity score falls within a pre-specified range of neighborhood of the propensity score of the treated unit. If the range of the neighborhood, i.e. the radius, is to be very small it is possible that some treated units are not matched because their neighborhood does not contain any untreated units. On the while, the smaller the size of the neighborhood the better is the quality of the matches. However, by using more untreated observations, one can increase the precision of the estimates, but at the cost of increased bias.

Secondly, radius matching (RM) involves all neighbors within a maximum propensity score distance (caliper), a priori defined, and thus corresponds to the common support assumption. Additionally, poor matches through too-distant neighbors are avoided (Dehejia and Wahbha, 2002; Smith and Todd, 2005).

3.1.1.1.3. Testing matching quality and overlap assumption

The "balancing properties" of the data was checked by testing that treatment and comparison observations had the same distribution (mean) of propensity scores and of control variables within grouping (roughly quintiles) of the propensity score.

The study was employed two types of balancing test. First a simple t-test was used to examine whether the mean of each covariate differs between the treatment and the control group after matching. Secondly, it was run logit using sample after matching and compare the pseudo R^2 with that obtained from the logit estimation using the sample before matching. As proposed by Smith and Todd (2005), if matching is successful, the after matching logit should have no explanatory power so that the pseudo-R^2 should be fairly low.

The methods to detect lack of overlap are to plot distribution of covariates by treatment groups and inspection of the propensity score distribution in both treatment and control groups. According to Imbens (2004), one obvious approach to check this assumption, is through visual inspection of the propensity score distributions, can typically give the researcher a good, initial reading of the extent to which there is overlap in the propensity score of the treatment and comparison units. In this study, lack of overlap was detected by plotting the distribution of propensity score and visually assess whether the overlap assumption holds.

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.

Standard bias: One suitable indicator to assess the distance in marginal distribution of the X variable is the standard bias (SB) suggested by Rosenbaum and Rubin (1985). It is used to quantify the bias between treated and control groups. For each variable and propensity score, the standardized bias is computed before and after matching as:

$$SB(X) = 100.\frac{\bar{X}_1-\bar{X}_0}{\sqrt{0.5(V_1(X)+V_0(X))}} \qquad (16)$$

Where $\bar{X}_1$ and $\bar{X}_0$ are the sample means for the treatment and control groups V1(X) and V0(X) are the corresponding variance (Caliendo and Kopeing, 2008). The bias reduction (BR) can be computed as:

$$BR = 100(1-\frac{B(X)after}{B(X)befor}) \qquad (17)$$

One possible problem with the SB approach is that one does not have a clear indication for success of the matching procedure.

Joint significance and pseudo R ^{2}: Additionally, Sianesi (2004) suggests re-estimating the propensity score on the matched sample, i.e. only on participants and matched non-participants, and comparing the pseudo- R^2 before and after matching. The pseudo- R^2 indicates how well the repressors X explain the participation probability. After matching there should be no systematic differences in the distribution of covariates between both groups and therefore the pseudo- R^2 should be fairly low. Furthermore, one can also perform a likelihood ratio test on joint significance of all covariates in the probit or logit model. The test should not be rejected before, and should be rejected after, matching. In our cases the combination of the above procedures were applied.

Bootstrapping: Standard errors in psmatch2 are invalid, since they do not take into account the estimation uncertainty involved in probit/logit regressions (pscore). One way to deal with this problem is to use bootstrapping as suggested by Lechner (2002). This method is a popular way to estimate standard errors in case analytical estimates are biased or unavailable. Recently it has been widely applied in most of economic literature in impact estimation procedures. Each bootstrap draw includes the re-estimation of the results, including the first steps of the estimation (propensity score and common support). Bootstrap standard errors attempted to incorporate all sources of error that could influence the estimates.

Sensitivity analysis: Matching estimators are not robust against 'hidden biases'. Different researchers become increasingly aware that it is important to test the robustness of results to departure from the identifying assumption. Estimation of treatment effects with matching estimators is based on the un-confoundedness or selection on observables assumption. However, if there are unobserved variables which affect assignment into treatment and the outcome variable simultaneously, a 'hidden bias' might arise. The size of the bias depends on the strength of the correlation between the unobservable factors, on the one hand, and treatment and outcomes, on the other (Rosenbaum, 2002).

The basic question to be answered here is whether inference about treatment effects may be altered by unobserved factors. In other words, one wants to determine how strongly an unmeasured variable must influence the selection process in order to undermine the implications of matching analysis. This is the main motive behind sensitivity analysis.

The bounding approach proposed by Rosenbaum (2002) in order to check the sensitivity of the estimated ATT with respect to deviation from the Constant Independence Assumption. The bounding approach does not test the confoundedness assumption itself. However, it provides evidence on the degree to which the significance of results hinge on this assumption. If the results turn out to be sensitive, the evaluator might have to think about the validity of his identifying assumption and consider other estimation strategies.

3.2. Variable Definition and Hypothesis

3.2.1. Treatment variable for PSM

Adopter (treatment) and non- adopter categories was identified based on the adoption of improved soybean variety. In this study, two years data (2014 and 2015) on area allocated to improved soybean variety was used to categorize the two groups. Adopters (participants) are those that allocated land to improved soybean varieties for two or more years while non-adopters (non-participants) are those who did not allocate land for this variety at all. It is equal to one if the farm household has adopted the variety and zero otherwise.

3.2.2. Outcome variable

Farm income (FARMICOM): It is a continuous variable, which refers to the annual total income obtained from farm output including soybean production.

3.2.3. Explanatory variables

Age of the farm household head (AGEHH): it is defined as the period from the respondent's birth to the time of the interview measured in years. It is a continuous variable. Those farmers having a higher age will have much better probability to adopt the improved soybean variety and increase its income due to experience obtained throughout his life time. Hossain and Crouch (1992) revealed that the probability of adoption of new farm practices increases with farmer's age in Bangladesh.

Sex of household head (SEXHH): This is dummy variable, which takes value of 1 if the head of household is male and 0 otherwise. Gender differentials in the farm household play a significant role in economic performance of a given household. One may expect that male headed households have more probability to adopt improved soybean variety than female headed households. This may be because male headed households have a chance to move and participate in different meetings and have opportunity to get more information. While female headed households are more preoccupied with childcare and home management than interaction with the external environment. According to Yenealem (2013) men are more likely to adopt improved variety than women. Therefore, it is hypothesized that sex of household head and adoption of improved soybean variety are positively related.

Level of education of the household head (EDUCTGRY): This refers to the number of schooling years attained by the respondents up to the time of the survey. According to Asfaw (2013) those farmers who have better level of schooling have high chance of being project participant. It is hypothesized that household heads that are literate have a better knowledge about improved varieties. This variable is a categorical variable and is expected to have a positive relationship with annual income. According to Alene (2000) level of education of the head of the household has a positive and significant influence on the adoption and use of improved maize variety with each additional year of schooling increasing the probability of adoption by 3.9%.

Family size (FAMSIZE): A continuous variable measured in numbers refers to the number of family members of a given household. The family members are important in the operation of farm activities, such as weeding, harvesting. Adoption of new technology often implies a need for additional labor. Family size contributes to the variation in the decision to adopt improved soybean variety. A research result reported by Solomon (2012) show that family size influences adoption positively. Therefore, it is hypothesized that family size is influence the adoption of improved soybean variety positively.

Farming experience (FARMEXP): Farming experience is measured in years. The study conducted by Solomon (2012) indicated that farmers experience was found to be significantly influenced the probability of adoption of barley variety**.** A positive influence of farming experience on the probability of adoption of improved soybean varieties is hypothesized.

Membership to cooperatives (COOPMEMR): membership to cooperatives represents whether a household is member to cooperatives or not. Cooperatives worldwide are committed to the concept of mutual self-help. This makes them natural tools for social and economic development, and provides significant additional benefit to communities and social systems. Formal as well as informal associations, such as indigenous cooperation groups, enforcing widely agreed standards of behavior, and uniting people with bonds of community solidarity and mutual assistance. As such, they embody important forms of social capital representing forums where in local communities can unit and act collectively Mekuria (2013). Membership to cooperatives also will increase households' access to services that might be granted by being member. This variable was expected to be positively related to adoption of improved soybean variety.

Market distance (MARKTDIST): It refers to distance from the residence of the farm household in kilometers to the market. Farmers near to markets have more information on price of agricultural commodities such as soybean compared to those away from the town. And can sell their products with better margin and transportation cost will be lower. The result of Berhanu *et al.,* (2014) revealed that, distance to market affects agricultural technology adoption decision of farm households negatively. Therefore, nearness to the market is expected to improve adoption of improved soybean variety and increase farm income of household.

Distance to the nearest road (DISTROAD): This is a continuous variable that is an average kilometers to main road. Proximity to main road has indirect effect on adoption of improved soybean variety. It was hypothesized that nearness to main road affects adoption of improved soybean variety positively.

Dependency ratio (DEPRATIO): It is a continuous variable and defined as the ratio of active to total family members. This ratio tells us the proportion of household members who are able to feed the dependent active members of the family. The more the dependency ratio in a household more of the production would be utilized for consumption rather than exchanged with improved soybean variety. Hence, it is hypothesized that this variable has negative influence on adoption of improved barley varieties. Tadesse and Belay (2004) reported the number of economically active family members is found to influence adoption of soil conservation mechanisms negatively and significantly.

Frequency of visit by extension agent (FRQNCVST): The number of times that the extension agents visit the farmer is determinant factor to technology adoption. Those farmers who are more visited by extension agents are expected to positively influence adopt improved soybean variety than rarely visited. Bingxin *et al.,* (2011) found that access to fertilizer and improved seed adoption was related to access to extension services.

Access to credit service (CREDIT): It is hypothesized that access to credit and adoption of improved soybean variety have positive relationship. The variable is entered in the model as a dummy variable (it takes a value 1 if the household has access to credit service and 0 otherwise). Geremew (2012) on his thesis analysis of smallholder farmer's participation in production and marketing of export potential crops: the case of sesame in Diga district, East Wollega zone of oromia regional state, those farmers who have access to credit service are more likely to produce significant amount of sesame than their counter parts.

Participation in demonstration (PARTDMRN): Demonstration is one of the means by which farmers acquire new knowledge and skills and it is measured by the number of times the farmer has participated in demonstration after improved soybean variety was introduced. Hence, participation in demonstration is expected to positively influence farmers' adoption behavior. Tesfaye and Alemu (2001) reported that participation in on-farm demonstration contributed positively to farmers' adoption decision.

Number of oxen owned (NBROXEN): It is a continuous variable to number of oxen owned by the households who own oxen have better chance to produce more. This is because oxen possession allows undertaking farm activities on time and when required. Therefore, it is expected that possession of oxen size increases the probability of adoption of improved soy bean and thereby increase farm income According to Solomon (2012) on his study the impact of livestock development program on farm household cash income: the case of Umbullo Wacho integrated watershed, Dore Bafano *Woreda* in Southern Ethiopia, households who do not own oxen are more like to participate in livestock development program.

Participation in training (PARTRAN): Training is one of the means by which farmers acquire new knowledge and skills and it is measured by the number of times the farmer has participated in training after improved soybean variety was introduced. Hence, participation in training was expected to positively influence farmers' adoption behavior. Minyahel (2007) reported that adoption of improved bread wheat was positively affected by participation in training.

Residence status (RSDCSTATS): Residence status is dummy variable if the farmer is indigenous to the region 1, otherwise 0. Being permanent residence of the woreda was expected to have positive relationship with adoption of improved soybean variety.

4. RESULTS AND DISCUSSION

4.1. Descriptive Analysis

4.1.1. Adoption status and major constraints in soybean production

In the area, the average improved soybean farm size of sample grower households was 2.91ha, and the maximum farm size was 12 ha and the minimum was 0.8 ha. The average quintal obtained was 6.47 quintal and the maximum was 85 quintal while the minimum was 0.75 quintal. The average gross income from improved soybean production of the sample adopter households from one season harvest during 2014/2015 production year was 3897.46 *birr.*

From the sample of the population 50% are non-adopters and 50% of them are adopters. Improvement in production and productivity of a given crop depends, among other things, on presence and use of better and improved varieties.

The landholding of the sample households ranges from 0.8 ha to 12.5 ha with an average figure of 1.51 hectares. The average livestock (including cattle, sheep, goats, pack animals, and poultry) was 3.45 TLU with the minimum and the maximum holdings of 0 TLU and 38.22 TLU respectively. The average labor force available was 6 man equivalents. Households generated cash income by selling crops (such as soybean, sorghum, maize, chickpea and noug) about 54% could do also from off-farm activities. About 72% had access to institutional credit to purchase farm inputs. The average distance from the nearest market place was 3.46 km with the minimum and maximum figures equal to 0.2 km and 8 km, respectively.

4.1.2. Descriptive statistics for socioeconomic variables in the study

A combination of different descriptive, the means and standard deviation and inferential, the t-test and X^2-test, statistics for explanatory variables of sample households were performed on the household level data to inform the subsequent empirical data analysis.

The descriptive and inferential results presented on Table 3 show that there was statistically significant difference between adopters and non-adopters in terms of distance to market, TLU, frequency of extension visit, farm income and oxen ownership in favor of the adopters

Table 2. Descriptive statistics of continuous independent variables

Variables	Mean across adoption categories		t-test	P Value
	Adopter	Non-adopter		
Distance to market	2.91	4.00	3.66***	0.0001
Age of household head	46.71	47.597	0.37	0.7087
Livestock holding(TLU)	4.22	2.52	2.50 **	0.0134
Family size	6.447	5.83	-.26	0.2096
Frequency of Visit	21.94	15.32	1.74 *	0.0825
Distance to main road	1.05	1.12	0.36	0.7131
Farm income	8.99	8.28	3.97***	0.0001
Farm experience	27.84	28.74	0.43	0.6689
Oxen ownership	1.16	0.5970	2.46 **	0.0148

Source: own survey, ***, **, and * indicates that at 1%, 5% & 10 significance level respectively

The descriptive and inferential statistics results presented in Table 4 show that 94.05% of adopters were male headed households. Regarding to participation in training 97.61% of adopters were participants of training and 84.52% of them were members of cooperatives. On the other hand, 94.03% of adopters and 76.22% of non-adopters participated in demonstration in 2014/2015 cropping season.

Table 3. Descriptive statistics of Dummy/ discrete Independent Variables

Variables	Percentage of adoption category Adopter	Non-adopter	χ2 value	p-value
Sex of household head			4.97**	0.026
-Male	94.05	79.10		
-Female	4.95	20.90		
Participation in training			35.47***	0.000
-Yes	97.61	53.73		
-No	2.39	46.27		
Cooperative membership			10.45***	0.001
-Yes	84.52	58.21		
-No	15.48	41.79		
Residence status			2.51	0.472
-Indigenous	31.34	35.8		
-settler	68.66	64.2		
Participation in demonstration			33.81***	0.000
Yes	94.03	76.22		
No	5.97	23.78		

Source: own survey (2017), ** and *** indicates 5% and 1% of significance probability level

4.2. Econometric Analysis

4.2.1.1. Propensity score matching (PSM*)*

This section presents the results of the logistic regression model which is used to estimate propensity scores for matching adopted households with non-adopters. As indicated earlier, the dependent variable in this model is binary variable indicating whether the household has adopted improved soybean or not and the outcome variable is the farm income. In the estimation, data from the two groups; namely, adopters and non- adopter households were pooled such that the dependent variable takes a value 1 if the household is adopter of improved soybean and 0 otherwise.

Table 7 shows the estimation results of the logit model. The estimated model appears to perform well for our intended matching exercise. The pseudo-R^2 value is 0.4571, which is fairly low. A low pseudo-R^2 value means that household adopted improved soybean do not have many distinct characteristics overall and as such finding a good match between adopters of improved soybean and non-adopters of improved soybean households becomes easier, and the pseudo-R^2 indicates how well independent variables explain the probability of adoption.

Table 4. Propensity score matching estimation (logit model)

Variables	Coefficient	Std. Err.	Z-value	P value
Sex of household head	0.9165	0.4418	2.07	0.0380**
Total family size	0.0189	0.0589	0.32	0.7490
Education category	0.1941	0.2341	0.83	0.4070
Religion of HH	-1.1022	0.3741	-2.95	0.0030***
Residence status of HH	-0.0724	0.2648	-0.27	0.7840
Distance to market	-0.1015	0.0290	-3.50	0.0000***
Distance to main road	0.1449	0.1377	1.05	0.2930
Cooperative membership	0.8185	0.3785	2.16	0.0310**
Dependency ratio	-0.1452	0.6119	-0.24	0.8120
Credit service	0.0005	0.0034	0.13	0.8930
Frequency of visit	-0.0044	0.0072	-0.61	0.5410
_cons	-3.3186	1.0639	-3.12	0.0020***
Number of obs	134			
LR chi2 (11)	84.90			
Prob > chi2	0.0000***			
Pseudo R2	0.4571			
Log likelihood	50.429			

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

Figure 4 portrays the distribution of the household with respect to the estimated propensity scores. In case of treatment households, most of them are found in partly the middle and partly in the right side of the distribution. On the other hand, most of the control households are partly found in the center and partly in the left side of the distribution.

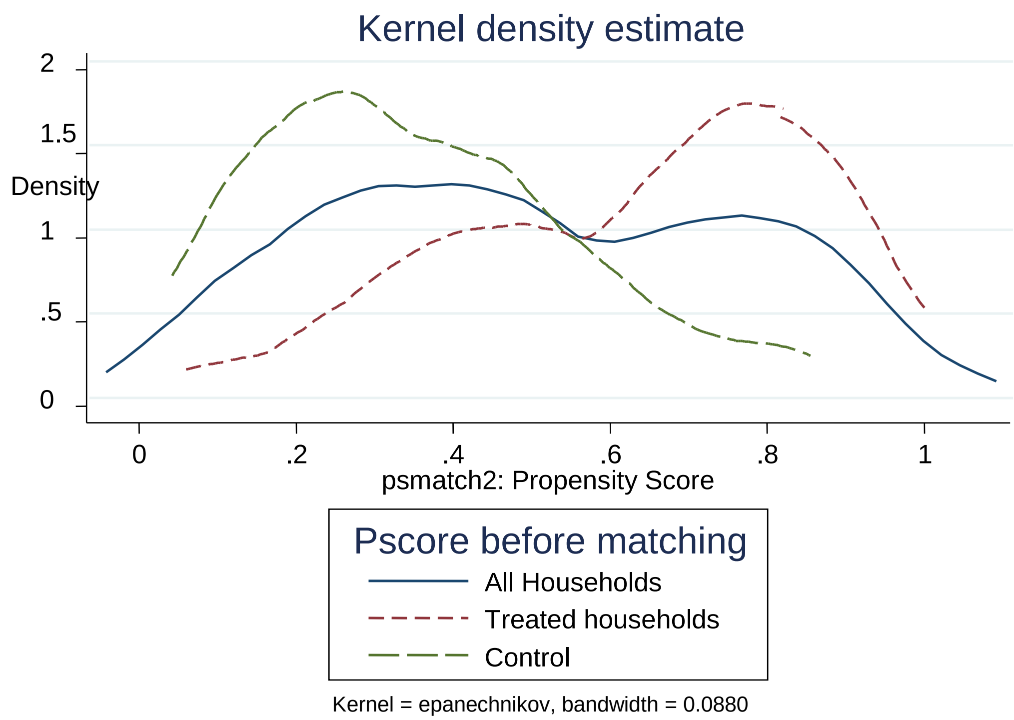

Figure 2. Kernel density of propensity score distribution
Source: own sketch (2016)
***,**, *, show significance at 1%, 5% and 10% level, respectively

Figure 4 portrays the distribution of the household with respect to the estimated propensity scores. In case of treatment households, most of them are found in partly the middle and partly in the right side of the distribution. On the other hand, most of the control households are partly found in the center and partly in the left side of the distribution.

4.1.1.1. Matching adopters and non-adopter households

The estimated propensity scores vary between 0.0692 and 0.9521, with a mean of 0.6404 for treatment households and between 0.0403 and 0.889181 with a mean of 0.3595, for control households (Table 8). The common support region would then lies between 0.04032 and 0.9521 that is the minimum and the maximum value of treated and control households, respectively. This ensures that any combination of characteristics observed in the treatment group can also be observed among the control group. In other words, households whose estimated propensity scores are less than 0.04032 and larger than 0.9521 are not considered for matching exercise. This is because no matches can be made to estimate the average treatment effects on the ATT parameter when there is no overlap between the treatment and non-treatment group (Bryson *et al.*, 2002). As a result of this restriction, 7 households from treated and 4 households from the control were discarded.

Table 5. Region of common support

Variable	Obs	Mean	Std. Dev	Min	Max
_pscore if AISV=1	67	0.6404	0.2283	0.0692	0.9521
_pscore if AISV=0	67	0.3596	0.2194	0.0403	0.8891
_pscore	134	0.5	0.2638	0.0403	0. .9521

Source: Own estimation (2017)

4.1.1.1. Choice of matching algorithm

Selecting matching estimator has its own criteria. The final choice of a matching estimator was guided by different criteria such as equal means test referred to as the balancing test, pseudo-R^2 and matched sample size (Deheia and Wahba, 2002). Balancing test is a test conducted to know whether there is statistically significant difference in mean value of per-treatment characteristics of the two groups of the respondent and preferred when there is no significant difference. Accordingly, matching estimators were evaluated by matching adopters and non-adopter households in common support region. Therefore, a matching estimator having balanced (insignificant mean difference in all explanatory variables) mean bears a low pseudo-R^2 value and also the one that results in large matched sample size is preferred.

Table 6. Performance of matching estimators

Matching Algorithm	Balancing test	Pseudo R2	Sample size
Kernel			
0.01	10	0.223	83
0.1	10	0.222	123
0.25	**11**	**0.222**	**123**
0.5	**11**	**0.222**	**123**
Caliper			
0.01	10	0.232	83
0.1	10	0.222	123
0.25	11	0.233	123
0.5	11	0.222	123
1	9	0.222	123
Neighbor			
1	9	0.222	123
2	6	0.224	121
3	6	0.222	123
4	87	0.224	122
5	10	0.222	123
Radius caliper			
0.01	11	0.230	83
0.1	**11**	**0.222**	**123**
0.25	**11**	**0.222**	**123**
0.5	10	0.233	123

Source: Own estimation result, 2017

The quality of matching can also be assessed by visual inspection using graphs. To do so, we plotted graphs of estimated propensity scores for adopted and non-adopter households both after matching. (Figure 5 and 6). Obviously, the distributions of the estimated propensity scores were somehow skewed to the right for adopter households and to the left for non-adopter households. However, the region of common support was ample and the distribution of the graph appeared even more similar after matching.

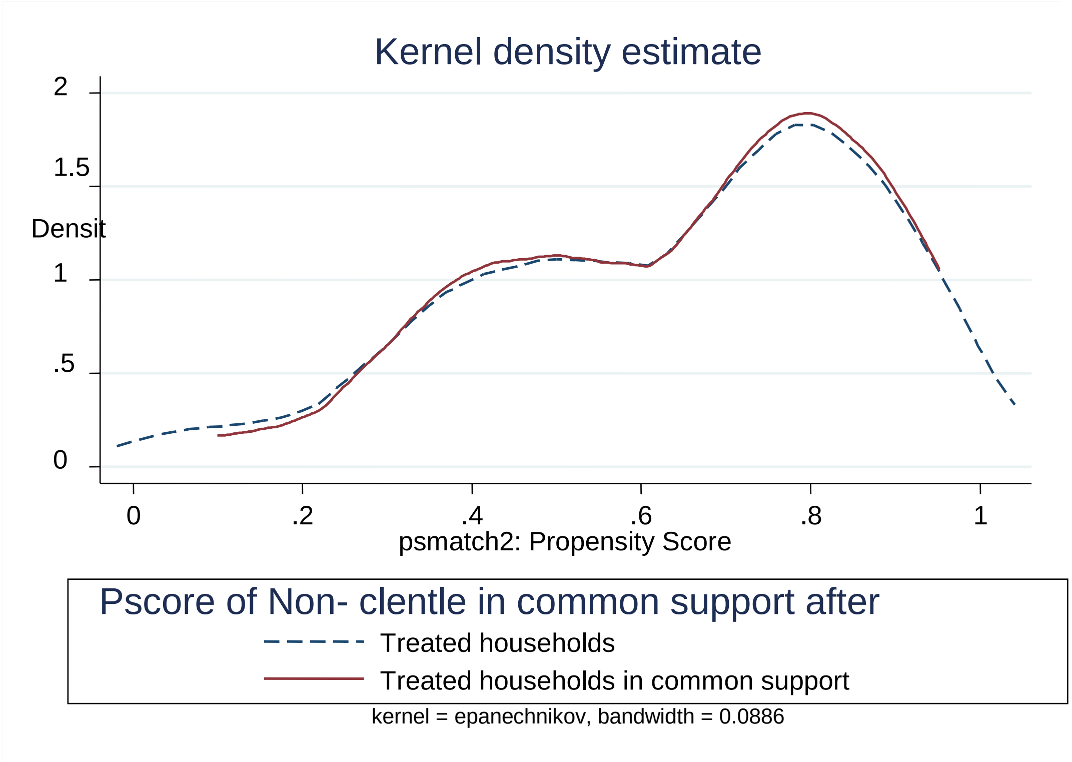

Figure 3. Kernel density of propensity scores of adopter households
Source: Source: own sketch (2017)

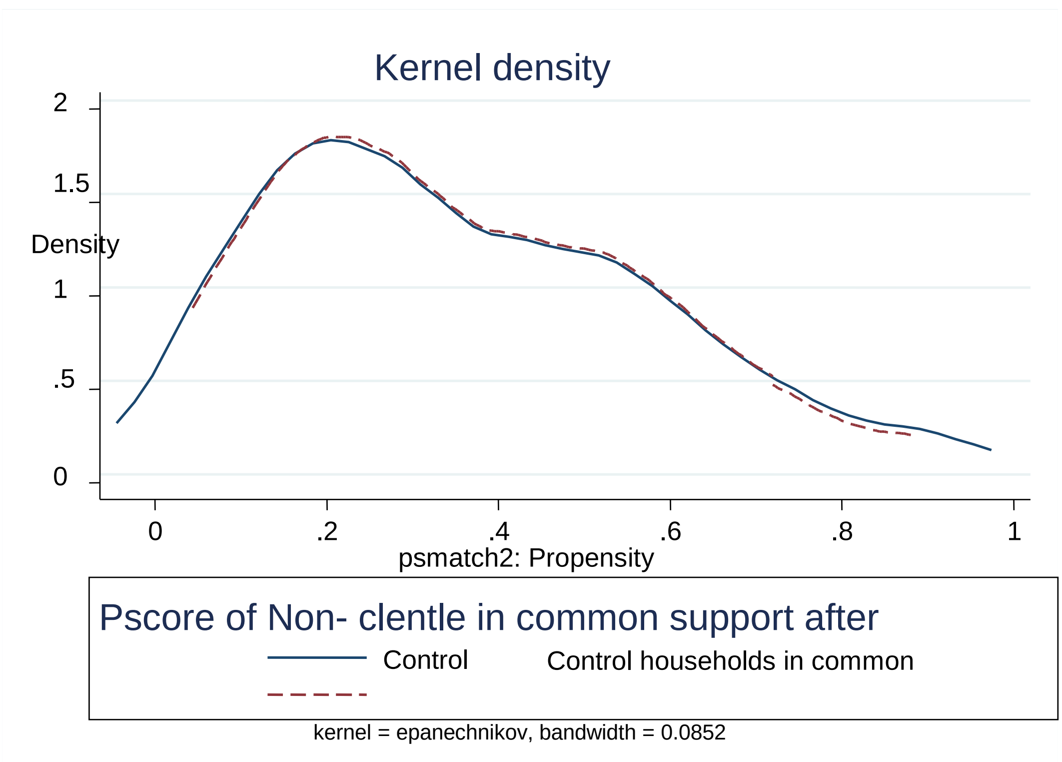

Figure 4. Kernel density of propensity scores of non-adopter households
Source: own sketch (2017)

4.1.1. Testing the balance of propensity scores and covariates

After choosing the best performing matching algorism the next step is checking balancing of propensity score and covariate using different procedures by applying the selected matching algorithm.

The mean standardized bias before and after matching are shown in the fifth columns of table 10, while column six reports the total bias reduction obtained by the matching procedure. In the present matching models, the standardized difference in Z before matching is in the range of 7.0% and 409% in absolute value. After matching, the remaining standardized difference of Z for all covariates lies between 0.9% and 16.8% which is below the critical level of 20% suggested by Rosenbium and Rubin (1985). In all cases, it is evident that sample differences in the unmatched data significantly exceed those in the sample of matched cases. The process of matching thus creates a high degree of covariate between the treatment and control samples that are ready to use in the estimation procedure.

Table 7. Propensity score and covariate balance

variable	Sample	Mean			
		Treated	Control	% bias	%red bias
_pscore	Unmatched	0.6404	0.3590	73.08	
	matched	0.5718	0.6073	15.9	78.3
Sex of household head	Unmatched	0.9254	0.7910	66.00	
	matched	0.9107	0.9026	4.1	96.52
Total family size	Unmatched	6.4478	5.8358	106.52	
	matched	6.4821	6.1201	7.0	87.90
Education category	Unmatched	1.6269	1.4328	76.37	
	matched	1.4643	1.4828	2.9	103.10
Religion of household head	Unmatched	1.5821	1.6269	-13.7	
	matched	1.5179	1.6365	-7.71	68.90
Residence status	Unmatched	1.7463	1.7612	-7.19	
	matched	1.7500	1.8039	-7.1	-215.70
Distance to market	Unmatched	10.3791	5.6642	409.00	
	matched	8.3821	9.6542	-8.3	103.50
Distance to road	Unmatched	1.0563	1.1261	-19.44	
	matched	1.0923	1.2670	-16.8	-22.26
Cooperative membership	Unmatched	0.8358	0.5821	110.00	
	matched	0.8214	0.7870	7.4	114.50
Frequency of visit	Unmatched	21.9403	15.3284	4.03	
	matched	20.4110	17.2790	3.6	99.37
Dependency ratio	Unmatched	0 .3213	0.0314	41.37	
	matched	0.3137	0.3115	0.9	97.9
Credit service	Unmatched	0 .3880	0.4328	-18.03	
	matched	0.4000	0.3875	2.5	113.8

Source: Own estimation result based on household responses, 2017

Table 11 presents the results of the joint significance of variables. The result show that after matching the pseudo-R^2 is fairly low and likelihood ratio tests are insignificant. This supports the hypothesis that both groups have the same distribution in the covariates after matching. The results clearly show that the matching procedure was able to balance the characteristics in the treated and the matched comparison groups. We, therefore, used these results to evaluate the effect of improved soybean adoption among groups of households having similar characteristics.

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

Sample	Pseudo R^2	LR chi^2	P>chi^2
Unmatched	0.475	84.90	0.000
Matched	0.222	8.20	0.695

Source: own computation (2017)

4.1.1.1. Treatment effect on the treated (ATT)

This sub-section provides evidence as to whether or not the adoption of improved soybean variety has brought significant changes on farm income. The radius caliper estimator with band width 0.1, the best matching estimator for the data at hand, was used to compute the average impact of improved soybean variety among adopter households.

Table 9.Average treatment effect on the treated (ATT)

Variable (*birr*)	Treated	Control	ATT	% gain	SE	T-value
Farm Income KM(0.25)	13596.33	12611.03	985.30	7.82	435.97	2.260**
Farm Income KM(0.5)	13597.24	12702.10	895.14	7.04	357.75	2.500**
Farm Income **RC(0.1)**	**13597.24**	**12479.10**	**1118.1**	**8.96**	**271.62**	**4.116*** **
Farm Income RC(0.25)	13597.24	12665.36	931.87	7.35	290.79	3.204***

Note: SE = Bootstrapped standard errors with 100 replications;

4.1.1.1. Sensitivity Analysis

Results on table 12 shows that the inference for the effect of the adoption of improved soybean variety is not changing though the participant and odds of being treated up to e^r =2(100%) in terms of unobserved covariates. That means for outcome variables estimated, at various level of critical value of gamma, the p-critical value are significant (i .e; there is no hidden bias due to unobserved confounder) which further indicate that we have considered important covariates that affected both adoption of improved soybean and outcome variable, farm income. In the analysis it set the maximum value for e^r =2(100%) with increment of 0.05. These values are a good starting place for many data sets in social sciences. Thus, we can conclude that our impact estimate (ATT) are not sensitive to unobserved selection bias and are a pure effect of adoption of improved soybean.

Table 1. Sensitivity analysis for unobserved biases

Gamma	e^r **=1**	e^r = 1.1	e^r =1.2	e^r=1.3	e^r=1.4	e^r=1.5	e^r=1.6	e^r=1.7	e^r=1.8	e^r=1.9	e^r=2
sig+	**0**	**0**	**0**	**0**	**0**	1.1e-16	1.0e-15	6.7e-15	3.6e-14	1.6e-13	6.2e-13

Source: Own estimation**,** 2017

5. SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

5.1. Summary and Conclusions

Soybean is among the cash crops which have been given priority in the national effort of meeting increased income and nutritional security of households. To this effect number of improved soybean varieties have been developed by the national research system and disseminated among smallholder farmers. Benishangul Gumuz region is one of the beneficiary regions of the country since 2006. The region has 156,000 ha of land that is suitable for soybean production. However, the contribution of the already disseminated varieties has not been well understood among the beneficiary farmers for informed decision making and to justify further expansion of soybean production zone in the region.

This study was conducted in Bambasi *woreda* of Benishangul Gumuz Regional State, which is located about 620 km away from Addis Ababa. In this area, soybean is an important crop, which serves as source of cash. New technologies that include improved varieties have been introduced by agricultural research centers and other non–governmental organizations. However, impact of the variety was not well studied in the study area.

The objective of this study was to provide empirical evidence to assess impact of improved soybean (*Bellessa-95*) variety on income of farm households. For this study, a total of 134 respondents from three kebeles were interviewed using semi-structured interview schedule. In this study, a three-stage stratified random sampling method was adopted to collect the required primary data. Focus group discussion and key informant interview was also conducted. Secondary data on basic agricultural activities and population was also collected from different stakeholders

Descriptive statistics such as mean, standard deviation, percentages, frequency, charts, and graphs, used to describe different categories of sample units with respect to the desired socioeconomic characteristics. Moreover, inferential statistics such as chi-square test (for categorical variables) and t-test (for continuous variables) were used to compare and contrast different categories of sample units with respect to the desired characters so as to draw some important conclusions. Propensity score matching models were used to analyze adoption and impact of improved soybean respectively.

The descriptive and inferential results show that there was statistically significant difference between adopters and non-adopters in terms of distance to market, TLU, frequency of extension visit, farm income and oxen ownership in favor of the adopters. 94.05% of adopters were male headed households. About 98% of adopters were participants of training in crop production and 84.52% of them were members of cooperatives. On the other hand, 94.03% of adopters and 76.22% of non-adopters participated in demonstration in 2014/2015 cropping season.

The estimation of the impact of improved soybean variety on farm income showed that sex of household head, religion of household head, distance to the nearest market and cooperative membership of household head have been the major factors of group difference.

After matching for household characteristics, it was found that, on average, adoption of improved soybean variety has increased annual income of households by 1118.1 *Birr.*

5.2. Recommendations

Based on the results of this research, the following core points are presented as recommendations in order to improve the application level and income gained from improved soybean.

Continuous training in improved soybean production**:** In order to increase farmer's income policy makers should devise more effective farmers' training mechanisms and provide more applicable improved soybean production mechanisms.

Promoting farmers to form or join cooperatives: Farmers should be encouraged to form cooperatives or join existing ones by government and non-governmental organizations to enhance their access to improved seeds and inputs.

Strengthening demonstration centers and Farmers Training centers (FTC): Forcing farmers to adopt any kind of agricultural technology will not bring the expected outcome rather it may aggravated their rigidity not to accept any new farming technologies. Therefore in order to improve farmers level of adoption of improved soybean as well as income extension workers and researchers should provide farmers with more practical trainings under farmers' direct participation in the demonstration centers.

Empowering female headed households to be participants: To increase and instigate the likelihood of adopting modern agricultural technologies like improved soybean by smallholder farmers, policy makers should put emphasis on empowering female headed households to be participants and agents of change by considering a comprehensive and an integrated development of the country where their involvement is pertinent in all endeavors of the country's overall development.

From the finding of the study adoption of improved soybean variety has a positive impact on farm income; therefore, scaling up and diffusion of improved soybean varieties in the study area should be broadened.

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