Impact of Food Security Package Loan on Food Insecure Households' Income and Asset Creation: The Case of West Belesa District, North Gondar Zone, Ethiopia

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Abstract: *Food security package loan has been found to be a critical instrument in order to improve the income of food insecure households. The main purpose of the program was to enhance the food insecure livelihood status through accessing of micro credit. Therefore, the objective of this study was to analyze the impact of Food Security Package Loan (FSPL) of micro credit service on the income and livelihood of food insecure households residing in West Belesa District. The study applied an econometric model of propensity score matching (PSM) to analyze the impact of FSPL on the income and livelihood of households based on data collected from a sample of 254 rural households (157 were food insecure and 97 food secure). The results of the econometric analysis display that FSPL participation significantly affects positively household's on-farm and off-farm income, employment, animal hold, saving and children participation in formal school. However, the food consumption level and types of house owned show no difference. This suggests that the stakeholders (government authorities, NGOs, aid agencies, etc) that deemed micro finance as a means to poverty reduction should take into account the implications of these indicator variables for better promotion of micro finance specifically FSPL and devise an intervention mechanism to further expand its impact towards improving food consumption and household asset building.*

Keywords: Food security package, income, Livelihood, West Belesa District

1. Introduction

Over the past one decade and half, Ethiopia has accomplished significant economic growth and progress. On average annual GDP growth was 10.3% between 2004 and 2012. During 2004 poverty rate of Ethiopian rural population was 38.9% that was down to 29.6% in 2012 (RESET, 2016). Ethiopian economy heavily depends up on the agriculture sector. It remains the largest contributor of an economy with a share of around 80% of the total labor force, 42% of the GDP and 70% of foreign exchange earnings of the country (NPC, 2016). The sector holds the key to creation of demand in other sectors of the economy and remains by far an important indirect contributor to the country's GDP. Hence the capacity of the economy to address poverty, food insecurity and other social-economic problems is highly related with the performance of this sector (EEA, 2013). Since Ethiopian agriculture is rain-fed and nature dependent, the production rate and productivity of the sector is insufficient to cover the consumption needs of food insecure beneficiaries of the country who live in moisture stressed areas. This suggests that persistent poverty and poor chronic status are common manifestation particularly in these areas (Askal, 2010; Meseret, 2012) and chronic food insecurity remains the main features for Ethiopian rural poor (Gilligan *et al*., 2009).

Understanding the importance and the roles of agriculture in the economy, the government of Ethiopia (GoE) has implemented Agricultural Development Led Industrialization (ADLI) policy since 1990s. ADLI adopts rural and agriculture centered development as a long term strategy to achieve rapid and sustained economic growth by making use of technologies that are labor intensive, but land augmenting (such as fertilizer, improved seeds and other agricultural practices). Basing on this overarching policy and strategy, the GoE has also devised several other economic development policies and strategies since 2002, including Rural Development Policy and Strategies, Sustainable Development for Poverty Reduction Program, food security program and establishment micro finance institutions both in urban and rural area. All these policies and strategies are in general designed to bring about rapid and sustained economic growth, guarantee maximum benefits to the majority of the population via addressing issues of poverty and food insecurity and promote the development of market oriented economy in Ethiopia (MoFED, 2003). Food security program collaborated with micro finance institutions to improve the food insecure households' income as well as their livelihood by financed their business activities.

As part and parcel of Food Security Program (FSP), starting from its inauguration in 2005, Productive Safety Net program (PSNP) includes resettlement, complementary community investment and recently Household Asset Building Program (HABP). As the second phase, according to Julie van and Coll- Black (2012), in 2009, Ethiopia has re-launched the FSP where Household Asset Building Program (HABP) replaced Other Food Security Program (OFSP), the later includes a demand driven extension, support component and improvements in access to financial services. It is argued that food security loan can play a major role in assisting the poor to move out of poverty by providing start–up capital which they have been unable to access historically because financial markets are underdeveloped and could not yet reach majority of the rural poor in most least developing economies (Getaneh, 2004).

However, still there is a debate in the academia and the literature of microfinance role in poverty reduction and food security. Some scholars argue that (despite claims about the role of microcredit in lifting the poor out of poverty, there is little agreement as to whether credit does borrowers more good than harm (Armendarize *et al*., 2010). In line with this, Ghalib (2007) suggests that poverty cannot be eradicated with small amount of money provided by micro finance institutions rather it implicates the poor in the long debt cycle.

Hossain (1988) and Mustafa (1996) found significant positive impacts of micro credit to alleviate poverty and food insecurity. Loan recipients showed higher income, capital accumulation, and value of house structure, children education, household nutrition and employments. On the other hand, Adams and Pischke (1992) found micro credit to be ineffective on the poor income and over all well-being status.

Despite these two opposing ideas, Food security package loan has been designed from 2010-2014 to provide micro credit through ACSI at subsidized interest rate at 10% and the non-subsidize interest rate at 15% to the food insecure beneficiaries to engage in different grave investment opportunities. In order to access micro credit to the food insecure beneficiaries, the program allocated 14 million birr for the district ACSI branch based on the total number of food insecure clients who live in the district (WBAO, 2016). The district ACSI branch has been giving microcredit services to the food insecure households based on the agreement made between ACSI and the district Agricultural Office. The district branch office has been addressing 2936 food insecure and food secured households and disbursed 16.02 million birr with average loan size of 4371.79 to 6777.14 birr minimum and maximum respectively (West Belesa Agricultural Office, 2016). Aiming to answer whether the food security program (FSP) achieved its objective that is expected from the microcredit service delivered to rural households in the study area, this thesis was conducted to analyze the impact of micro credit on food insecure households' income and livelihood change in West Belesa district. It also aimed to identify the timeliness of credit disbursement period and the time when the food insecure households require credit.

2. Research Methodology

2.1. Description of the study area

The study has been conducted in West Belesa District at North Gondar Zone of Amhara National Regional State, Ethiopia. It is among the chronically food insecure Districts in the region where the FSP has been implemented since 2005. The District comprises 30 administrative *kebeles* including Arbaya town. Among which 19 are food insecure *kebeles*. As seen in the map Figure1, the blue colored is food insecure and the green ones are food secure *kebeles* classified based on the exposed to drought and unable to cover annual food consumption level. 19 out of 30 *kebeles* are the food insecure *kebeles.*

West Belesa District is located at about 706 km North of Addis Ababa and about 82 km of Gondar town. It is bordered on the south LiboKemkem, on the west Gondar Zuria, on the East by East Belesa, and on the North by Wogera District. The district is found in the Tekeze lowland sorghum and goat livelihood zone (TSG). Its agro-ecology is predominantly *Kolla* covering 59.8 %, followed by *Woina Dega* 38.7% and *Dega* 1.5%. The topography is mainly characterized by plateau with a share of 50%, mountains 40%, and hilly 10% of the total land of the District West Belesa District of Agriculture Office (WBDoA, 2016). It is largely covered with small vegetation of bushes and shrubs. The economy of the district is mixed farming largely participated on crop production, followed by livestock rearing which has a special importance among wealthier farmers. Its altitude ranges 1100 to 2350 meter above sea level while the annual temperature ranges between 13^{0}C and 35^{0}C. The mean annual rainfall ranges 800-1200 mm. Its population in year 2016 was 192,336, of which 95,156 (49.47%) are males and 16,100 (8.37%) are food insecure ones (Ibid).

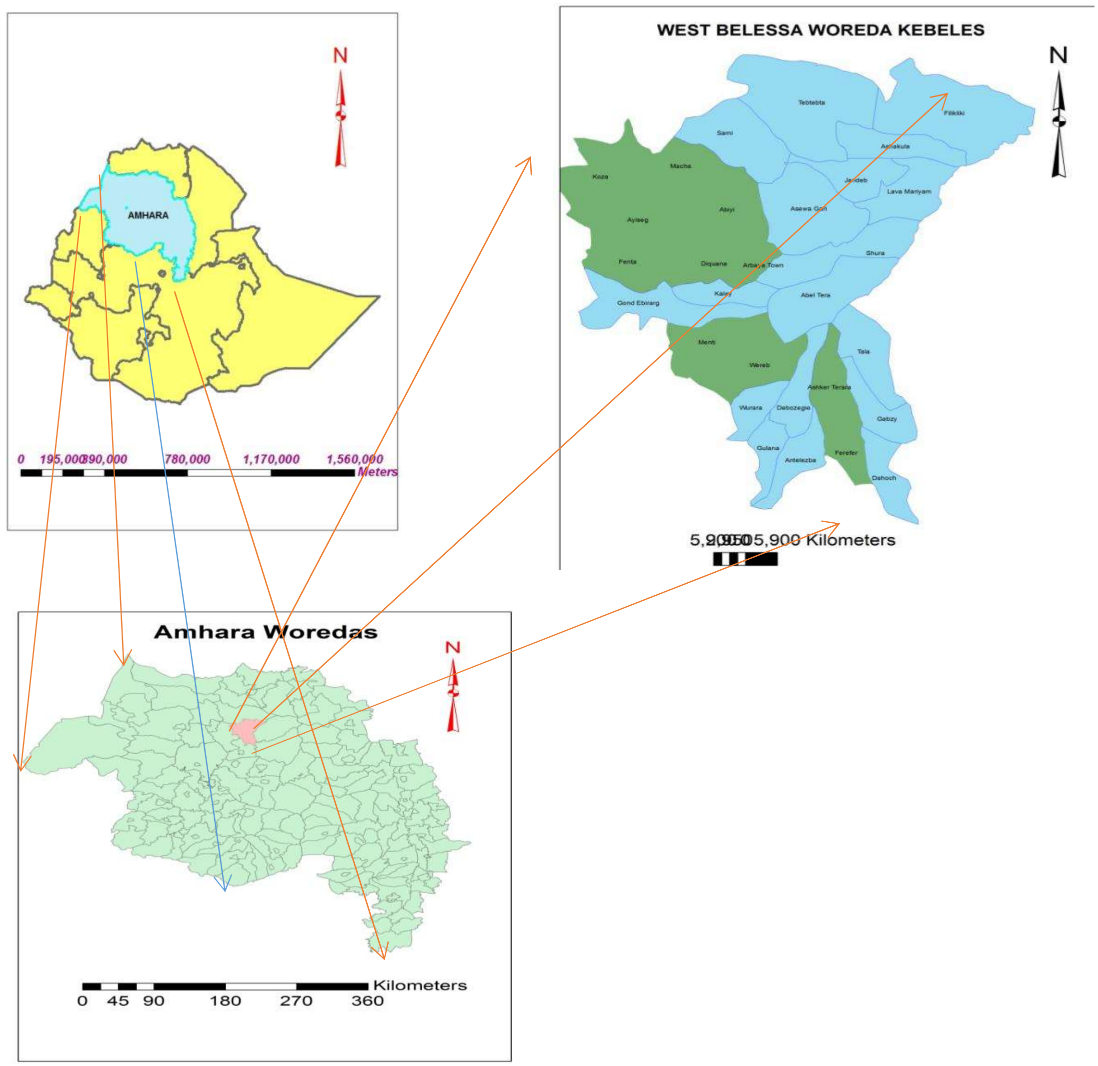

Figure 1. Map of the Study Area

2.2. Sample size and method of sampling design

To determine the size of the sample, this study adopted the following formula developed by Yemane (1967) as he assumed (P = 0.5) that the most variability of the population would be covered.

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

Where: n = statistically acceptable sample size

N = Total size of target population

e = level of precision (error level) at 95%, confidence level (0.05).

West Belesa district has thirty *kebeles*. The thirty *kebeles* have clustered in to two based on their food secure status. 19 *kebeles* were food insecure and 11 *kebeles* were food secure *kebeles*. Two *kebeles* from food insecure/Gulana and Wurarakebeles/ and two *kebeles* from food secure *kebeles*/ Kozi, and Menti kebeles were selected by using random sampling technique from 19 food insecure and 11 food secure *kebeles,* respectively. 2936 food insecure households from food insecure *kebeles* who have been received credit and 3250 food secure households' from food secure *kebeles* who have not been received credits were target for this study to control the spillover effect of credit (WBDAO, 2016).

The sample numbers of population for each *kebele* were determined using probability proportion to size and sample respondents from each *kebele* were selected using systematic random sampling technique. Based on this sampling technique 254 sample households', 157 credit users from food insecure households from food insecure *kebele* and 97 non-credit users from food secure households from food secure *kebele* were selected.

Table 1. Food security status of sampled households and credit use status

Kebeles	Population Size (N)		Sample Size (n)		Actual Respondents
	Food insecure/ credit users/	Food secure/ non-credit users/	Food insecure/credit users/	Food secure/ non-credit users/	
Gulana	450	0	102	0	**102**
Wurara	390	0	55	0	**55**
Koza	0	265	0	63	**63**
Menti	0	185	0	34	**34**
Total	840	450	157	97	254

Source: Own Survey data (2017)

2.3. 2.3 Methods of data analysis

2.3.1. Propensity score matching (PSM)

According to Khandker *et al.* (2010) impact evaluation is the act of studying whether the changes in well-being are indeed due to the intervention and not to other factors. The main aim of FSP package loan was to increase and diversify the income sources of food insecure households. To this effect, there is a need to see whether the intervention of FSP package loan has significant influence on the participant households or not. However, to compare them with and without intervention difference, baseline survey was not conducted prior to the intervention of the FSP in the study area. Therefore, this study uses PSM method because PSM is the appropriate method when such kind of problem arises. Following Caliendo and Kopeinig (2005), there are some steps in implementing PSM. These are: PSM estimation, choosing matching algorithm, checking for overlap (common support), matching quality (effect) estimation and sensitivity analysis.

2.3.2. Propensity score estimation procedure

Propensity score estimation is the first step in PSM technique. When estimating the propensity score, two choices have to be made. The first one concerns the model to be used for the estimation, and the second one the variables to be included in this model. In principle any discrete choice model can be used. Preference for logit or probit models (compared to linear probability models) derives from the well-known shortcomings of the linear probability model, especially the unlike of the functional form when the response variable is highly skewed and predictions that are outside the [0, 1] bounds of probabilities. For the binary treatment case, where estimated the probability of participation versus non-participation, logit and probit models usually yield similar results (Caliendo and Kopeinig, 2005). For this study, logit model was used to estimate propensity score.

Regarding, the choice of variables Smith and Todd (2005) suggested that economic theory, a sound knowledge of previous research and also information about the institutional settings should guide the researcher in building up the model. However, concerning the inclusion (or exclusion) of covariates in the propensity score model. The matching strategy builds on the CIA, requiring that the outcome variable(s) must be independent of treatment conditional on the propensity score. Hence, implementing matching requires choosing a set of variables X that credibly satisfy this condition.

According to Gujarati (2004), in estimating the logit model, the dependent variable is participation which takes a value of 1 if the household participated in a program and 0 otherwise.

The mathematical formulation of logit model is as follows:

$$Pi = \frac{e^{Zi}}{1 + e^{Zi}} - - - - - - - - -2$$

Where: -

Pi = i^{th} household probability of food in secure who participate in the credit market which takes value 1 otherwise it takes 0

$$Zi = \alpha + \beta Xi + Ui \quad - - - - - - - - - 3$$

Where I= 1,2,3, … N

α = Intercept

β = regression coefficient to be estimated

Xi = Explanatory variables

Ui = a disturbance term

The effect of household's participant in the credit market on a given outcome(Y) is specified as $Yi = \mathrm{y}(\mathrm{D} = 1) - \mathrm{Y}(\mathrm{D} = 0) - - - - - - - - - 4$

Where Ti = a treatment effect (effect due to participation of food insecure HHs in credit),

Yi = is the outcome on the i^{th} household

Di = is whether the i^{Th} household has got the treatment or not

However, Y (Di = 1) and Yi (Di = 0) cannot be observed for the same HHs simultaneously, estimating individual treatment effects Ti is impossible and one has to shift to estimating the average treatment effects of the population than the individual one. The most commonly used average treatment effect estimation is the average treatment effect on the treated (T_{ATT}) which was E (T/D = 1) = E [Y (1) / D = 1] – E [Y (0) / D = 1] specified as follow:

$$TATT = \mathrm{E}\left(\frac{\mathrm{T}}{\mathrm{D}} = 1\right) = \mathrm{E}\left[\mathrm{Y}\frac{(1)}{D} = 1\right] - \mathrm{E}\left[\mathrm{Y}\frac{(0)}{D} = 1\right] - - - - - -5$$

Since the counter factual mean for those being treated, E (Y (0) / D = 1) is not observed, there is a need to choose a proper substitute for it to estimated ATT. Though it might be thought that using the mean outcome of untreated individuals' (y (0)) /D=0) as a substitute to the counter factual mean for these being treated, E (Y (0) / D = 1) is possible, it is not a good idea especially in non-experimental studies. This is because it is likely that components which determine the treatment decision also determine the outcome variables of interest.

In our particular case, variable those determine HHs participation in the credit market affects HHs income and employment generation. Therefore, the outcomes of individuals from treatment and comparison group would differ even in the absence of treatment leading to a self-selection bias. However, by rearranging and subtracting E(y(0) / D 0) from both side of equation 6 T_{ATT} can be specified as

$$E = \left[\mathrm{Y}\frac{(1)}{D} = 1\right] - \mathrm{E} = \left[\mathrm{Y}\frac{(0)}{D} = 0\right] = \mathrm{TATT} + \mathrm{E}\left[\mathrm{Y}\frac{(0)}{D} = 1\right] - \mathrm{E}\left[\mathrm{Y}\frac{(0)}{D} = 0\right] - - - - - 6$$

In the above both terms in the left hand side are observables and ATT can be identified if no self-selection bias. That is if and only if E (y (0) however this condition can be ensured only in a randomize experiments (i.e. where there is no self-selection bias. Therefore, some identified assumptions must be introduced for non-experimental studies to solve the selection problems.

Basically there are two strong assumptions to selection problems those are

- Conditional independence assumption
- Common support condition

Conditional independence assumption

The CIA is given as $Y0Y1 \perp D/ X, \forall X$ ----------------------------- 7

Where ⊥ indicates independence

Xi = a set of observable characteristics

Yo = non participation

Y1 = participants

Given a set of observable covariates (X) which are not a affected by the treatment / in this case food insecure HHs who receive credit/, potential outcomes are increasing of their income, employment engagement, saving of food insecure HHs are independent of treatment assignment / independent of how the borrowers and non-borrowers of food insecure HHs will be selected.

The implication of CIA assumption is that the selection is solely based on the observable characteristics (X) and variables that influence assignment? Participation in credit/ and potential outcomes change of income, own productive assets, smoothing consumption and engagement in different income generating activities are simultaneously observed (Bryson *et al*., 2002; Caliodo and Kopeinig, 2005). Hence after adjusting for observable difference, the mean of outcomes is similar for D = 1 and D = 0. Therefore, $E(Y0 / D = 1, X) = E(Y0 / D = 0, X)$.

3. Results and Discussion

3.1. Food insecure household time of credit demand

The food security package loan encompasses a suite of activities which have been designed to enhance the agricultural production, food security and the asset accumulation capacity of the rural households. This program therefore mainly served the food insecure households by providing a subsidized credit for the purpose of purchasing packages, based on the business plan developed. In the first evaluation of food security program, Gilligan *et al*. (2007) noted that except Tigray region access to package loan was low. As seen Table 2, 0, 42.68, 56.69, and 0.64% of the 157 food insecure households was applied to get credit from Micro finance institution (MFI) in the 1st, 2nd, 3rd and 4th quarter respectively and while 96.9, 1.03, 2.03and 0% of the 97 food secure households applied to get credit in the respective quarter. Out of these credit users only 11.46, 73, and 66% of the food insecure households received credit at the 2nd, 3rd and 4th quarter respectively. As indicated in the proposal thesis, credit which were disbursed to the users during the 2nd and 3rd quarters were considered as on time and would contribute income increasing of the food insecure households according the interviewer response. This may be due to the fact that all the inputs for different income generating activities (such as, crop products, livestock to start either petty trade or rearing and fatting) at rural community level are available relatively at cheaper prices during these quarters whereas during 4th quarter all inputs for different income generating activities at rural community level is scarce and hence relatively expensive during this quarter and partly would affect negatively the credit users' annual income according the interviewer response. However, 42.04% of the food insecure households have received their credits lately and would affect their annual income negatively according the interviewer response. As illustrated in the chi-square test statistic, there is statistically significance difference at 1% level of significance between the Food insecure and the food secure households in terms of applying and receiving their package loan. 42.04% of the food insecure households receive credit lately whereas the food secure get credit on time mean on this thesis starting from quarter 1 up to quarter 3 considered on time disbursed of credit.

Table 2. Food insecure household period of credit request and received by quarter

Variable	Attribute	Food insecure HHs		Food secure HHs		Total		Chi-square
		N	%	N	%	N	%	
Request Quarter	1st quarter	0	0.00	94	96.91	94	37.01	241.53***
	2nd quarter	67	42.68	1	1.03	68	26.77	

	3rd quarter	89	56.69	2	2.06	91	35.83	
	4th quarter	1	0.64	0	0.00	1	0.39	
	Total	157	100.00	97	100.00	254	100.00	
Received Quarter	1st quarter	0	0.00	94	100.00	97	38.19	254***
	2nd quarter	18	11.46	1	1.03	19	8.12	
	3rd quarter	73	46.50	2	2.06	74	30.80	
	received lately	66	42.04	0	0.00	66	25.98	
	Total	157	100.00	97	100.00	254	100.00	

Source: Own Survey data, (2017)

*, **, *** Statistical significance level at 10, 5 1% respectively

3.2. Results of econometric analysis

According to Rosenbaum and Rubin (1993), PSM is the conditional probability of assignment to a particular treatment given a vector of observed covariate. In this study PSM was used to estimate the impact of food security package loan on the food insecure households' annual income in the study area. In addition, PSM helps control pro-intervention difference on the covariates. Logistic regression model was applied to estimate propensity scores for matching program Food insecure households with Food secure households. In the estimation process, households were pooled in such a way that the dependent variable takes a value 1 if the household is participant and 0 otherwise.

Table 3. Definitions of explanatory variables and expected sign

Variables	Definitions of variables	Expected sign
HH Part	=1 if a household participated in FSPL	+
Age	Age of household head measure in year	-
Sex	= 1 if the household head is male	+
Edu	Education level the household head measured in year	+
Mohh	Marital status of household head with three categories, taking unmarried/single as base category	
	Married =1 if the household head is married	+
	Divorced =2 if the household head is divorced	_
HHAE	Household's labor force of adult equivalent	+
Agriexn	Agricultural extension contact	+
Own land	Cultivated own land	
Busskills	Participation of on off farm = 2, on farm = 1 and both = 3	+

Source: Own description of variables (2017)

VIF for continues variables and contingency coefficient for dummy variables were calculated in order to detect the presence of strong multi-collinearity problem among the covariates. As shown in table 4 except own land and labor force the other covariates had no serious problem of multicollinearity. Consequently, own land and labor force was dropped from the estimated model to avoid biased estimation. In addition, robust standard errors were estimated using Breusch-Pagan test to detect hetroscedasticity on dummy variables.

After checking multicollinearity and heteroscedasticity assumptions of regression model, the propensity score or the likelihood of participation for a given household is estimated using logit model where the dependent variable is program participation and taking six pre-intervention covariates as independent variables. It was found that the estimated model appears to perform well for our intended matching exercise.

As shown in Table 4, 3 out of 8 covariates significantly affect the program participation decision of households in the study area. The interest of the matching procedure is to get participant households from non-participants with similar probability of participation given the explanatory variables. If the number of explanatory variables affecting the participation decision is limited, it created a good opportunity for matching and it makes the matching procedure less difficult since matching algorism is implemented to eliminate significant differences of explanatory variables between Food security package loan participant HHs and Food security package loan participant HHs.

Table 4. Logistic regression model estimation of household participation decision

Covariates	Coff.	Std. Err.	T-value	P-Value
Age	0.010672	0.011323	0.94	0.346
Sex				
Male	-0.01498	0.428724	-0.03	0.972
Edu	-0.04023	0.07194	-0.56	0.576
Msohh				
Married	-0.27222	0.658687	-0.41	0.679
Divorced	-0.92528	0.675476	-1.37	0.171
HHAE	-0.29089**	0.127915	-2.27	0.023
Agriexn	0.178278	0.365503	0.49	0.626
Own land	0.570152**	0.23023	2.48	0.013
Busskills	0.843868***	0.164754	5.12	0.000
_cons	-1.13393	0.823166	-1.38	0.168

Source: Own Survey data (2017)

*, **, *** Statistical significance level at 10, 5 1% respectively

The test statistics in Table 4 indicates the participation of food security package loan was strongly influenced by own land holding, labor force and business skills, which have positive and significance influence on the participation decision of a given household. This may be the fact that people with large number of own land may need additional capital besides their own financial capital to run business through accessing other associated factor inputs for exploiting the larger sized land or participate in income generating activities. This in turn facilitates the participation decision of households.

3.3. The common support condition

The other required criterion to match the treated with untreated households is to find out the common support region. There are two approaches to map a common support region for the propensity score distribution; these are minima & maxima, and trimming approaches (Caliendo and Kopeinig, 2005). Leuven and Sianesi (2003) however recommend the use of both the common and "trimming" approaches at the same time for the identification (imposition) of a common support. Even though recommended to use both approaches together, in evaluation studies using PSM, the approach that yields good match is preferred.

After defining the common support region, those observations in the common support region have been matched with the other group and others which were not in the common support region were out of further consideration. The estimated propensity scores in Table 5 vary between 0.17 and 0.95 (mean = 0.67) for food security package loan participant households and between 0.21 and 0.92 (mean = 0.53) for non-participant (control) households. Based on the minima and maxima criteria, the common support region would then lay between 0.21 and 0.92. In other words, households with estimated propensity scores less than 0.21 and greater than 0.92 would not be considered for the matching exercise.

Table 5. Distribution of estimated propensity scores

Group	Observation	Mean	Std. Dev.	Min	Max
Food insecure HHs	157	.6739897	.1761324	.1712023	.9544923
Food secured HHs	97	.5276662	.1684542	.2130317	.926299
Total households	254	.6181102	.1870027	.1712023	.9544923

Source: Own survey data (2017)

*, **, *** Statistical significance level at 10, 5 1% respectively

In a similarly manner, Figure2 shows the distribution of the propensity score for total households, food security package loan participant and non-participant households. In case of treatment households, most of them were found in the left and middle part of the distribution. On the other hand, most of the control households were partly found in the center and partly in the right side of the distribution. Since most of the participant and non-participants' households are located in the middle of the distribution, it makes the matching procedure simple.

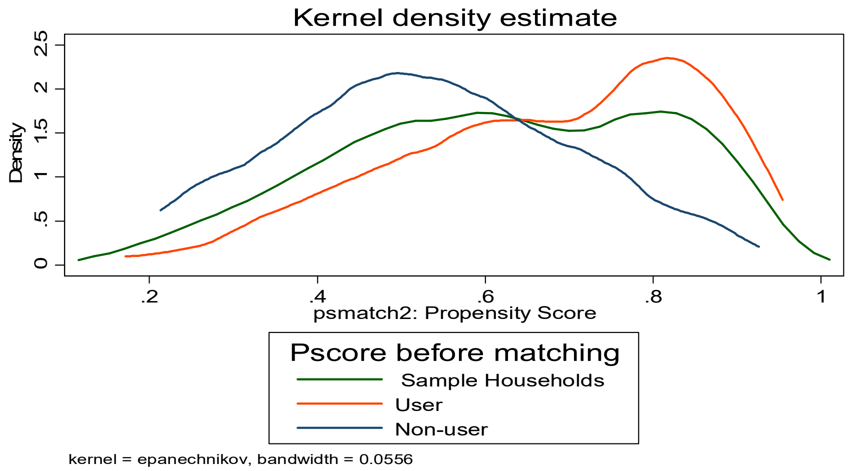

Figure 2. Kernel density of propensity score

As shown in Figure 2, most of the observations lay in the right middle part of the graph with the mean propensity score value of 0.61. 2 out of 157 observations below the maxima criteria are out of the common support region and hence he/she is disregarded from further consideration. The density of distribution of the propensity scores for non-participants of the project on the other hand shows that observations with the probability above the minima criterion fail to lie on the common support region. Accordingly, none of the observations from the non-participants ignored from further consideration.

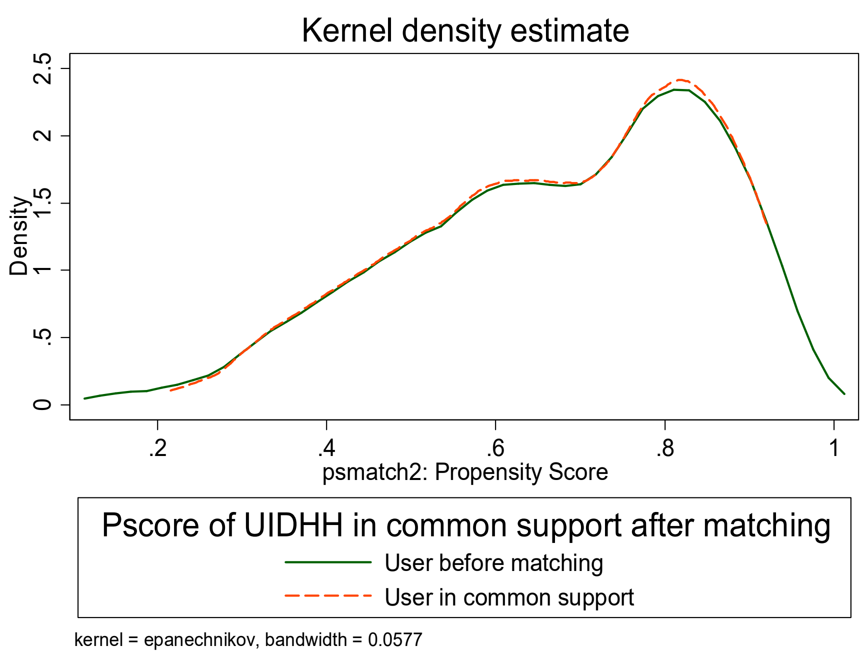

Figure 3. Kernel density estimate of p/scores of participants with and without common support

Figure 3 shows the distribution of treated households with respect to the estimated propensity scores, where the largest and dotted lines graph indicates the treatment households in the common support region, the line graph on the dot indicates the treated households after matching.

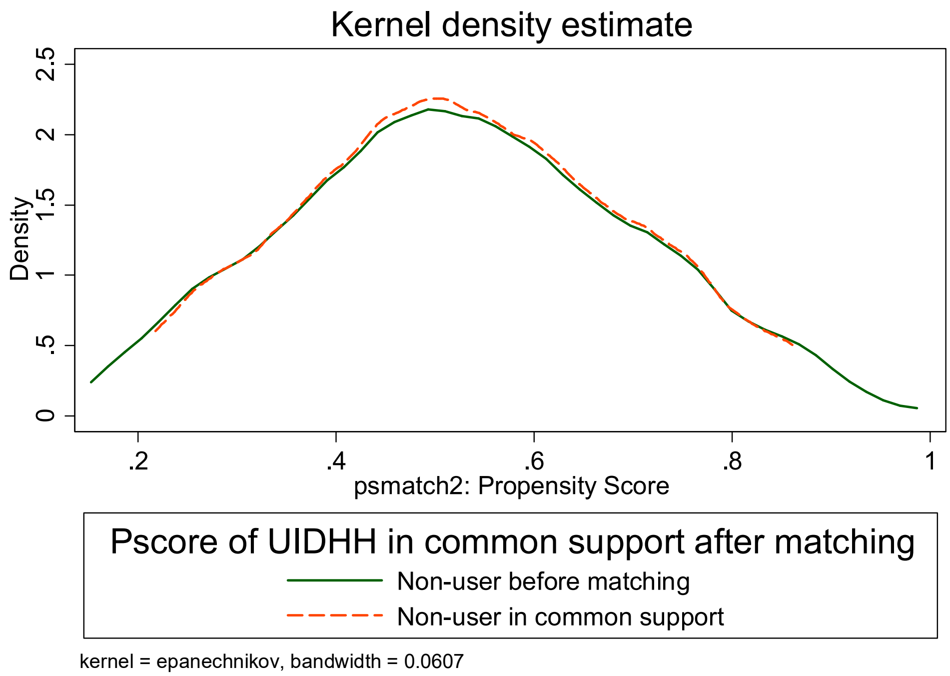

Figure 4. Kernel density estimate of propensity scores of non-participants' households with and without common support

Figure 4 shows the distribution of control households with respect to the estimated propensity scores after matching, when the largest and dotted lines graph indicates the control households in the common support region, the line graph on the dot indicates the control households after matching.

3.4. Matching of participant and non-participant households

Estimators of PSM have different match quality but the choice of matching estimator is decided based on the balancing qualities of the estimators. The final choice of a matching estimator was guided by different criteria such as equal means test referred to as the balancing test (Dehejia and Wahba, 2002), pseudo-R^2 and matched sample size. Specifically, a matching estimator which balances all explanatory variables (i.e., results in insignificant mean differences between the two groups), bears a low R^2 value and also results in large matched sample size is preferable.

Here balancing test means is a test conducted to know whether there is a statistical significant difference in the mean values of covariates before and after matching. The preferred estimators are the higher the number of covariates with equal mean after matching. Keeping other selection criterion, the balancing test indicates the quality of the matching algorithm implemented.

3.5. Selection of best algorithm

Table 6. Performance of matching estimators under the three criteria

Matching Estimator	Performance criteria		
	Balancing test*	Pseudo R2	Matched sample size
Radius Caliper matching			

With 0.01 band width	6	0.1169	135
With 0.1 band width	6	0.1169	173
With 0.25 band width	6	0.1169	180
With 0.5 band width	6	0.1169	192
Kernel Matching			
With 0.01 band width	**6**	**0.1169**	**214**
With 0.1 band width	6	0.1169	**252**
With 0.25 band width	6	0.1169	**252**
With 0.5 band width	6	0.1169	**252**
Neighbor matching			
1 neighbor	6	0.1169	194
2 neighbor	6	0.1169	**252**
3 neighbor	6	0.1169	**252**
4 neighbor	6	0.1169	**252**

Source: own survey data (2017).

* indicates the number of explanatory variables with no statistically significant mean differences between the matched groups of program and non-program households.

According to the criteria outlined above, kernel type with band width 0.01, 0.1, 0.25 and 0.5 have given similar results except large sample size compare to others. As compared to other alternative matching estimators indicated in Table 6 they have relatively similar or low pseudo R^2 with best balancing test (all explanatory variables insignificant) and large matched sample size. Therefore, matched samples by kernel either with band width of 0.01 satisfies the property of balanced matching for all of the covariates. Accordingly, the kernel matching algorism with band width of 0.01 has been used for this research to compare PSNP participants and non-participants with respect to the impact indicators.

Table 7. Balancing test of matched sample

Variable				Mean			T-test	
	Food insecure	Food secure HHs	T-test	Food insecure	Food secure HHs	%bias	T	p>t
_pscore	0.67399	0.53	0.4	0.67399	0.67308	0.5	0.05	0.963
Age	45.9682	44.85	0.94	45.968	45.478	3.4	0.31	0.757
1.sex	0.7579	0.67	-0.03	0.75796	0.84076	-18.3	-1.84	0.067
Edu	0.8472	0.83	-0.56	0.84713	2.3057	-68	-3.65	0
HHAE	2.1940	2.39	-2.27**	2.194	2.1287	5	0.43	0.668
1.msohh	1.1019	1.21	-0.41	0.74522	0.72611	4.2	0.38	0.702
2.msohh			-1.37	0.17834	0.0828	23.1	2.53	0.012
Agriexn	0.8598	0.79	0.49	0.85987	0.77707	21.9	1.91	0.057
Ownland	1.0299	0.92	2.48**	1.0299	1.0502	-2.5	-0.22	0.825
Busskills	2.1273	1.53	5.12***	2.1274	2.0637	6.9	0.57	0.568

Source: Own Survey Data (2017)

*, **, *** Statistical significance level at 10, 5 1% respectively

As shown in Table 7 the balancing tests of covariates, before and after matching; participant and non-participant households were significantly different in terms of certain pre-intervention characteristics. However, these differences were removed after the matching was conducted.

3.6. Impact of food security package loan on income and livelihood of food insecure households

Table 8. Impact of food security package loan on income of food insecure households

Outcome variables	Food insecure HHs	Food secure HHs	Difference	S.E.	T-stat
On farm income	150228.0161	6385.22639	8842.78974***	845.117489	10.46
Off farm income	3320.6129	1534.24162	1786.37128***	613.313856	2.91
Animal holding TLU	2.89	1.94	0.95***	0.23	4.11
Farm Land rent (ha)	0.21	0.11	0.10**	0.04	2.75
Saving (birr)	348.65	157.35	191.29***	47.94	3.99
HH House	0.35	0.36	-0.01	0.06	-0.11
Sending children (Number)	1.32	0.99	0.33**	0.16	2.00

Source: Own Survey data (2017)
*, **, *** Statistical significance level at 10, 5 1% respectively

The food insecure household experience is mixed farming of crop production and animal rearing to generate their annual income. When they gained credit they allocated to purchase of animals for rearing and fattening purpose and trading. Annual income status improvement of food security package loan users can be explained by using variables like on-farm income, off-farm income, expenditure on food consumption and non-food consumption, livestock holding in (TLU), in rented farming land (Ha), engagement in income generating activities, saving part of their income, types of their house standard and number of children attending formal education.

The statistical evidence presented in Table 8 revealed that there is a significant difference on Food insecure HHs and Food secure HHs in the on-farm income, off -farm income, Animal holding (TLU), Saving in birr, engagement in business activities, land rented in ha and sending of the children to formal education. The analysis has proved that, Food insecure HHs were better-off than the Food secure HHs in on-farm and off-farm income by running of on-farm and off-farm packages by about 8842.78 and 1786.78 birr respectively. This is due to the fact that Food insecure HHs was more exposed to participate in business activities thinking to repay their credits. The results also show Food insecure farm households cultivated in rented land has increased by 0.1 ha. Improvement in income has direct effect on saving of money on financial institutions as a result the saving amount of money of the Food insecure HHs were higher than Food secure HHs by an average amount of birr 191.29 during the study period. The animal holding (TLU) of the Food insecure HHs were greater than their counterparts by 0.95 TLU. This is because most Food insecure HHs participated in the on-farm activities particularly rearing and fattening of livestock to increase and diversify their income. In case of sending their children to formal education they have also shown an improvement by 0.33 in number over their counterparts. This is may be the fact that they are more exposed to business activities and social services that forced them to learn their children to formal education.

3.7. The sensitivity analysis of food security package loan

Table 9. Result of sensitivity analysis using Rosenbaum bounding approach

No.	Outcomes	$e^{y}=1$	$e^{y}=1.25$	$e^{y}=1.5$	$e^{y}=1.75$	$e^{y}=2$
1	On farm income	P<0.000	P<0.000	0.000	0.000	0.000
2	Off farm income	P<0.000	P<0.000	0.000	0.000	0.000
3	Animal holding in TLU	P<0.000	P<0.000	0.000	0.000	0.000
4	Saving money in birr	P<0.000	P<0.000	0.000	0.000	1.1e-16
5	Rented land in ha	P<0.000	P<0.2.2e-16	7.0e-14	3.7e-12	7.5e-11

6	Child education	P<0.000	P<0.000	0.000	0.000	0.000

Source: Own Survey data (2017)

e^y (Gamma) =log odds of differential due to unobserved factors where Wilcoxon significance level for each significant outcome variable is calculated.

Table 9 presents the critical level of e^y (first row), at which the causal inference of significant food security package loan impact has to be questioned. As noted by Hujer *et al.* (2004), sensitivity analysis for insignificant effects is not meaningful and is therefore not considered here. Given that the estimated food security package loan effect is positive for the significant outcomes, the lower bounds under the assumption that the true treatment effect has been under estimated were less interesting (Becker and Caliendo, 2007) and therefore not reported in this study. Rosenbaum bounds were calculated for food security package loan impacts that are positive and significantly different from zero. The first column of the table shows those outcome variables which bears statistical difference between treated and control households in our impact estimate above. The rest of the values which corresponds 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 e^y. Results show that the inference for the impact of the food security package loan interventions is not changing though the participants and non-participant households have been allowed to differ in their odds of being treated up to 100% (e^y= 2**)** in terms of unobserved covariates**.** That means for all outcome variables estimated, at various level of critical value of e^y, the p- critical values are significant which further indicate that we have considered important covariates that affected both participation and outcome variables. We couldn't get the critical value e^y where the estimated ATT is questioned, which is similar value compared to the value set in different literatures which is usually 2 (100%).Thus, we can conclude that our impact estimates (ATT) are insensitive to unobserved selection bias and are a pure impact of food security package loan interventions programs.

4. Conclusion

This study tried to analyze the timeliness of food security package loan disbursement period to food insecure households and its effect on their annual income generating. To determine whether the food insecure households access credit timely or not, the study set an indicator that show timeliness of credit disbursement. Accordingly, credit is timely disbursed if and only if the food insecure households' gained their credit request as requested in the 2nd and 3rd quarter otherwise it is lately disbursed and affect their annual income negatively.

Based on the survey results, 99.34% of the credit users requested their credit on 2nd and 3rd quarter. Even though 99.34% of food insecure household request in 2nd and 3rd quarter only 57.96% of them accessed their credit on time. The rest 42.04% were accessed lately and affects their annual income generating due to increase cost of inputs in the 4th quarter.

Another objective of this study was to analyze the impact of credit on food insecure annual income sources. Concerning the econometric results, seven explanatory variables had hypothesized to analyze the impact of food security package loan on households' income. The logit regression model showed that the six variables have significant effects on incomes of households. All of the variables significantly improve households' income. These variables are on- farm and off-farm annual income, animal holding, saving, and rented farming land and sending children to formal education.

To access the food security package loan timely implementer bodies and stakeholder should identify the demand of beneficiary and work closely accordingly. In addition to Non- Governmental and Governmental Credit providers, private company should initiate to provide credit to rural area to fill the gap of financial demand of rural areas.

In general, the model output shows that the food security package loan has positive impact on food insecure households' income and livelihood. Therefore, the program should have to be given emphasis for further integration of concerned government bodies, food security offices and private sectors.

Conflict of interest

The authors declare that there is no conflict of interest to publish the manuscript in the journal.

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