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Article

Adoption of Chemical Fertilizer Technology and Household Food Security, in Southern Ethiopia, in Case of Soro District in Hadiya Zone

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Abstract: Adoption of chemical fertilizer technologies is a prerequisite for achieving sustainable agricultural development. However, the link between chemical fertilizer technology adoption decision and food security remains poorly understood due to lack of comprehensive measures of food security. Therefore, this study attempts to investigate the factors affecting chemical fertilizer technology adoption decision, intensity of employing and its impact on the food security in Soro district, southern Ethiopia. A cross – sectional field survey was conducted among 382 cereal crop growers in Soro district in 2019 cropping season. Descriptive statistics and econometric methods such as probit regression, Heckman two stage and propensity score matching was developed for the data analysis. The results of probit regression revealed that the technology participant was significantly affected by size of family, education, family labor force, livestock holding, credit service, extension service, information, distance to market, distance to road and non-farm activity. Intensity of the technology significantly influenced by sex, size of family, family labor force, educational, marital status, membership to cooperative, extension service, access to credit and livestock holding. The findings suggest that the role of technology adoption at farm level due to higher yield and income could translate in to reduced poverty. Rural development office, extension office, and another concern body should give an important attention to adoption decision which is base for enhancing yield. Expansion in the level of adoption would consequently improve welfare economy.

Keywords: Chemical fertilizer; food security; intensity; probit regression; Propensity score matching.

1. Introduction

Agriculture plays a crucial role in enhancing economic growth, achieving food security and poverty alleviation in Less Developed Countries (LDCs) in general and Sub-Saharan Africa (SSA) in particular [1, 2]. Poverty alleviation, yield and income growth can mainly be achieved by agricultural growth. Agricultural sector is the development tool, means, methods and techniques for enhancing Millennium Development Goals in 2015, despite the sector creates spillover effects to the remaining sectors [3]. This is due to low adoption of agricultural technology such as chemical fertilizer technology and techniques. Agricultural technology can be described as the integration of people, knowledge, tools, means of creating new tools serving humans and their environment, systems and decision to make full application of an innovation with the objective to improve people's lives [4]. Production and productivity in agriculture slow down and rural poverty increase due to attention is not given to the use and adoption of agricultural technologies and techniques [5]. However, majority of smallholder farmers depends on traditional methods of production; this has lowered the level of productivity due to low technological adoption, low chemical fertilizer utilization, decreased soil fertility, unreliable climatic conditions, poor infrastructure, environmental degradation and land scarcity. According to the study of [6], results revealed that adoption agricultural technology enhances income resulting from higher cereal crop yields.

Technological change in agriculture holds high yielding variety of seeds, fertilizers, plant protection measures and irrigation. These changes in agricultural sector increase the productivity per unit of land and bring about rapid increase in production. Ethiopia is a country with a population of more than 100 million and agriculture is basis for the country's food security and the livelihoods of nearly 85% of its people [7]. Agriculture is the backbone of the Ethiopian economy, playing an important role in the country's economic development. The sector accounts for 50% of the GDP and generates 90% of export earnings, 85% employment of the country's labor force and it also accounts 70% of raw materials requirement of the country's industries. Agricultural sector showed the lower growth rate of 2.3% in 2015/16 [8]. Increasing productivity through expansion of chemical agricultural technology is a key, if not the only the strategy option to increase production. The adoption and diffusion of chemical fertilizer have become an important issue in the development-policy agenda for Sub-Saharan Africa [9], especially as a way to tackle land degradation, low agricultural productivity and poverty. Slow development of agriculture sector could be constraint for the rest of the economy if it is not efficient enough to supply food and raw materials to the industrial sector.

Since more than 85% of the population lives in the rural area of Ethiopia where agricultural sector is the main source of their livelihood and growth is a major source of poverty reduction. Hence, Ethiopian government formulated policies and strategies with high priority for agricultural sector, in order to accelerate agricultural growth and striving for agricultural productivity to achieve food security, poverty alleviation and rural development [10]. Agricultural technology can contribute towards increasing food production, agricultural and rural incomes, entails positive spillovers to other sectors and contributes to economy wide growth. Although, agriculture is a strong option for spurring growth, overcoming poverty and enhancing food security in Ethiopia; it has poorly performed in terms of production and productivity for the past four decades [11]. According to [12], the backwardness of the agricultural technology used is the major responsible for the poor performance of Ethiopian agricultural sector. Hence the current Ethiopian government and policy makers strongly believe that agricultural sector is a key fundamental for growth and transformation so as to overcome poverty alleviation and food security. Hence, the government has initiated agricultural expansion packages and extension programs to promote the adoption of farm level new technology. The current government has given prominent attention to the role of chemical fertilizer in ensuring food security [13]. But according to [14], only 30% to 40% of Ethiopian smallholder farmers use fertilizer, and those farmers do only apply on average 37 kg/ha to 40 kg/ha, significantly below recommended rates which is 300kg/ha. Adoption of the chemical fertilizer in the Soro district has shown improvement recently though still not sufficient. In 2015/2016 harvest year the adoption rate is expected to reach about 56.7% and the intensity of use is far from the recommend level. In line with the Ethiopian transformation plan this is not satisfactory. A key tenet to achieve the agricultural growth target in the GTP_{II} was the adoption of improved technologies, because in the plan agricultural output growth takes the leading attentions which can be achieved through intensive use of modern inputs such as chemical fertilizer.

Agricultural productivity can be ensured by adopting modern agricultural technologies to produce higher per unit of land through by using agricultural inputs and expanding the area under cultivation to meet expected rising agricultural productivity demand. Advanced agricultural technology tends to enhances output and reduces cost of production which in turn increases agricultural gains in farm income [15]. Adoption of agricultural technology increase agricultural yield [16]. According to the study of [17], the results revealed that the most common areas of agricultural technology development for cereal crops were new varieties and management regimes; soil fertility management; weed and pest management; irrigation and water management. Adoption of new agricultural technologies creates higher earnings and lower poverty, improved nutritional status, lower staple food prices and increased employment opportunities.

Factors determining adoption of chemical fertilizer can be categorized as demographic, institutional, economic and social factors. Different study identifies determinant factors in relation to their specific study areas. According to their studies [10,18 – 22], used Probit and Tobit models to institutional, economic and social variables in the study area of central Mid-hills of Nepal, vihiga in west Kenya, Tanzania and (west Shewa, Babile district and West Wollega) of Ethiopia were significantly influence smallholder farmer's adoption and decision of chemical fertilizer technology. Their studies revealed that the age, level of education, access to extension services, irrigation facilities, yield, access to credit, size of landholding, distance of the chemical fertilizer store, access to farm inputs and output market, use of animal dung, land renting out, oxen ownership, value cost ratio, number of family size, perception of farmers about cost of inputs and off farm income were significantly influenced the smallholder farmer's adoption and intensity chemical fertilizer technology.

Many studies done on chemical fertilizer technology adoption decision, according to their studies demographic, institutional and socio-economic factor influences smallholder farmer's decision to participate chemical fertilizer technology adoption. [18, 23, 24], using panel probit and bivariate probit model. Their studies found the variable like: Sex, age, educational level, farming experience, yield superiority, participation on crop production training, access to extension services, irrigated farm size, tropical livestock unit, farmers' perception of yielding capacity, taste preference for improved crop varieties, active labor ratio, distance to the nearest market, maturity period of new varieties and use of improved cereal crop varieties were significantly influences adoption and intensity of chemical fertilizer technology. Different chemical fertilizer technology adoption and intensity studies were undertaken in less developed countries and many parts of Ethiopia [19, 22, 25 – 30]. However, most of their studies were limited in dealing with identifying the factors influencing adoption decision of the framers and its impact on crop yield. Thus, the present study was expected to provide recent empirical evidences on factors determining chemical fertilizer technology adoption among smallholder farmers.

In low income countries, enhancing the livelihoods of smallholder farmers depends highly on low agricultural productivity due to agricultural technology adoption such an improved agricultural technology influences farmer's income and yields [6, 31]. Modern agricultural inputs such as high yield varieties and chemical fertilizer have been the important agricultural inputs to increase cereal crop production and productivity so as to improve the living standards of smallholder farmers. This is important in Ethiopia whose people highly depends on subsistence farming and lies below poverty line. Regarding to the use of new agricultural technologies depends such as fertilizer, improved seed, and herbicide very low among smallholder farmers, place and skill. The chemical fertilizer utilization in most African countries including Ethiopia is near to zero, while it exceeds 50kg/ha in China and Egypt [32]. This study attempts to investigate the factors affecting chemical fertilizer technology adoption decision, intensity of employing and its impact on the food security in the study area. In particular, the study focuses on assessing the impact of chemical fertilizer technology on smallholder farmer's food consumption expenditure which is a key indicator of household food security. Hence, there was limited empirical studies has been done concerning the influencing factors of chemical fertilizer technology adoption, intensity of employing and impact on household food security.

Therefore, this study was designed to identify demographic, institutional and socio-economic factors that influence the smallholder cereal crop farm household chemical fertilizer adoption decision and extent of adoption, and its impact on food security in the study area.

2. Materials and Methods

Description of the study area

The study was conducted in Soro district. The district is located in Hadiya Zone in southern Ethiopia and lying between 7⁰23′00″ and 7⁰46′00″ North Latitude and 37⁰18′00″ and 37⁰23′00″ East Longitudes. The district has an altitude that ranges from 840 to 2850 meters above sea level. Gimbichu is capital of the district is about 260km away from Addis Ababa and 32km southwest from hosanna. The district comprises 46 rural kebeles, 3 rural towns and has total population of 229,617 of which 114,489 (48.86%) are male and 115,128 (50.18%) are female. Out of the total population, 14% are urban dwellers. The district has a population density of 222km^2 and average landholding farm family is 0.4ha and has a total area of 58,061ha. According to Soro Woreda agricultural and rural development office reports 2015/16 the district has three basic agro ecological zones: namely; Dega (14.2%); Woynadega (53.1%) and Kola (32.7%). The mean annual rainfall in the area was 1260mm and average temperature was 19^{0}c. Farming system of Soro district is mixed crop and livestock farming; thus, both crop and livestock contribute their share to the farmers' agricultural income. The main types of crops grown are wheat, teff, barley, maize, sorghum. Soro district is one of the main surplus grains producing area of the Hadiya Zone and wheat and teff is the main cash crop too.

Sampling techniques

A multi stage sampling procedure was developed to select the sample kebeles and sample households. The study applied both non-probability and probability sampling techniques to select the sample from a given population. In the first stage: Out of the total 11 district of Hadiya Zone, Soro district was purposively selected, because of its introduction and application of chemical fertilizer technology. In the second stage, take into account the resource available, six kebeles (Shonkola, Kecha, Bure, Sundusa, Kosha and Danetora) were selected based on their agro ecological zone. In the third stage a list of smallholder farmer was prepared for each selected Kebele and sample respondents were selected by simple random sampling method. Sample size was determined and allocated to each selected kebele through proportionately. The survey was carried out in the months of May and June 2019. The sample size for the smallholder farmers survey was determined as: n = $\frac{Z^2 p(1-p)}{e^2}$ [33] where: N_i is total number of observation in ith kebele; n is the total number of households in one kebele; N is the total number of households in six Kebeles; N_S is the total number of sample size; e is level of precision (5%) and z is level of confidence for 95% is (1.96). Based on above formula, the calculated sample size is 382 farm smallholder farmers (n = 382).

Table 1. Distribution of sample size by kebele and adoption status.

Kebele	Number of households (N)	Probability Proportional Sample (PPS) Size				
		Adopters		Non- adopters		Total Sample (n_i)
		N_a	n_a	N_{na}	n_{na}	
Shon kola (Kebele$_1$)	533	223	25	310	34	59
Kecha (Kebele$_2$)	592	252	26	340	35	61
Bure (Kebele$_3$)	663	288	28	375	37	65
Sundusa (Kebele$_4$)	556	240	26	316	34	60
Kosha (Kebele$_5$)	672	300	30	372	37	67
Danetora (Kebele$_6$)	680	310	30	370	40	70
Total	3696	1613	165	2083	217	382

Note: n_i= total number of households selected from kebele I (I = 1, 2, 3, 4); N_i= total number of households in kebele i; N_a = Total number of adopters; N_{na}=Total number of non-adopters; n_a = adopting households selected; n_{na} = non-adopting households selected

Data collection

The data for study was collected from both primary and secondary sources. Cross- sectional data was developed from the randomly selected sample farmers. For the primary data collection, specifically questionnaires were designed and pre-tested based on the objective of the study. The questionnaires schedule was tested at the farm level on 32 randomly selected smallholder farmers. In the light of pre-testing, essential amendments were made on the wording and statements. Furthermore, the pre-test enables to know whether smallholder farmers have clearly understood the interview schedule. Secondary data was collected from relevant literatures, reports of agricultural and rural development offices and other publications. After, this both quantitative and qualitative information was collected to respond for raised questions around studying area as well as chemical fertilizer technology adoption and intensity.

Methods of data analysis

In this study the data were analyzed by using descriptive statistics such as mean, standard deviation, percentages, frequency, t- test, Chi-square and graphs. Furthermore, it was assumed that smallholder farmers who cultivate cereal crop may or may not apply chemical fertilizer in cereal crop cultivation. Therefore, the dependent variable in this model is dummy of two outcomes, yes (1) or no (otherwise). In this case, the use of Ordinary Least Square (OLS) technique for such variables poses inference problems, and thus not appropriate for investigating dichotomous or limited dependent variables. In such circumstances, maximum likelihood estimation procedures such as logit or probit models are generally more efficient [34].

Several investigators used different models for analyzing the determinants of technology adoption at farm level. Various adoption studies have used Tobit model to estimate adoption relationships with limited dependent variables while the others used double-hurdle model. However, it is conceivable to use [35] two step procedure in case of anticipated problem of selection bias in the sample. Selection bias was anticipated in this study because among the representative not all smallholder farmers are believed to participate in fertilizer adoption due to individual problems. The Heckman two-step selection model allows for separation between the initial decision to participate chemical fertilizer technology ($Y > 0$ *versus* $Y \leq 0$) and the level of their application. The model uses in the first step a probit regression to assess the probability of decision to participate, in the second step uses ordinary least squares (OLS) to determine the intensity of participation [36] and the method correct sample selection bias. This technique used in order to control the selectivity bias, endogeneity problem and to obtain consistent and unbiased parameter estimates [36]. In selection model procedure, sample bias is determined by the relationship between the residuals of the two stages (stage 1 and stage 2). Estimates are biased if the residuals in the stage 1 and 2 are correlated. Similarly, Stage 1 does not affect stage 2 results if the residuals are unrelated. Positive and negative correlations between residuals are indicated respectively by positive and negative mu (μ) values, which is the correlation between error terms of two regression model. The first stage Heckman two steps or the probit model that analyzes the factors determining the probability of chemical fertilizer adoption decision specified as:

$$pr\ (Y_{1i} = 1/X_{1i},\ \beta_{1i}) = \Phi\ (f\ (X_{1i},\ \beta_{1i})) + \varepsilon i \quad \ldots\ldots (1)$$

Where; Y_{1i} is an indicator variable that is equal to unity for chemical fertilizer user smallholder farmers; Φ is the standard normal cumulative distribution function; X_{1i} is variable that affect adoption decision; $\beta 1i$ is a coefficient to be estimated. The variable $Y1i$ takes the value 1 if the household use chemical fertilizer and 0 otherwise. This can be shown mathematically:

$$Y_{1i}^* = \beta_0 + \beta_{1i}X_{1i} + \varepsilon i \quad \ldots\ldots (2)$$

$$Y_{1i} = 1\ if\ Y_{1i}^* > 0 \text{ and } 0\ if\ Y_{1i}^* \leq 0 \quad \ldots\ldots (3)$$

Where; i = 1, 2, 3... n, $Y_{1i}{}^*$ is a latent variable of marginal utility the farmer's get from adoption of chemical fertilizer input, β_0 is Constant term, εi is error terms in the first stage model assumed to be normally distributed with zero mean and constant variance ($\sigma 2$). In the second stage parameters can consistently be estimated by OLS by incorporating an estimate of the inverse Mills ratios denoted as λ_i from probit regression model as additional explanatory variable as specified bellow: -

$$Y_{2i} = \alpha_0 + \alpha_i X_{2i} + \mu_i\, \lambda_i + vi \quad \ldots\ldots (4)$$

Where: Y_{2i} is the quantity fertilizer applied per hector, X_{2i} is implies the explanatory variables influencing the level of chemical fertilizer applied shown in (table 5), α_0 is the Constant term in OLS regression model, α_i is the Parameters to be estimated in the second stage, λ_i is the inverse mills ratio computed from first stage estimation, μi is implies the Correlation between first and second stage error terms or corr. (εi, vi), vi is the error terms in the second stage.

According to [35], the IMR (λ_i) is a variable for controlling bias due to sample selection. This term is constructed using the model in the probit regression (first stage) and then incorporate into the model of the second stage (OLS) as an independent variable can obtain: -

$$\lambda_i = \frac{\emptyset(\beta 0 + \beta 1iX1i)}{\Phi(\beta 0 + \beta 1iX1i)} \quad \text{.......... (5)}$$

Where, Ø (.) denotes the standard normal probability density function and Φ (.) denotes the cumulative distribution function for a standard normal random variable. But the value of λ_i is not known, the parameters β_0 and β_{1i} can be estimated using a probit model, based on the observed binary result. Then the estimated IMR calculated as: -

$$\widehat{\lambda \mathrm{i}} = \frac{\emptyset(\widehat{\beta 0} + \widehat{\beta 1}X1i)}{\Phi(\widehat{\beta 0} + \widehat{\beta 1}X1i)} \quad \text{.......... (6)}$$

Propensity Score Matching applied when program participation is none randomly assigned. It evaluates the treatment effect in case of two groups treated and untreated individuals. In non-experimental economic data, we observe whether individuals were treated or not, but in absence of random assignment must be concerned with differences between the treated and non-treated [37]. The PSM method creates a statistical control group of individuals without chemical fertilizer that has similar observable covariates to the treated group, i.e. individuals with chemical fertilizer adopter. Thus, the control group is generated which will be observationally the same to the treated group after matching.

With matching methods, one tries to create a control group that is as similar to the treatment group as possible in terms of observed characteristics. The intention is to find, individuals who are observationally similar to treated individuals from large group of non-treated who are observationally similar to participants in terms of characteristics not affected by the program (these can include preprogram characteristics, for example, because those clearly are not affected by subsequent program participation). Different approaches are used to match participants and nonparticipants on the basis of the propensity score. They include nearest-neighbor (NN) matching, caliper and radius matching, stratification and interval matching, and kernel matching and Local Linear Matching [38].

The procedure of calculating ATT based on propensity score match method is similar with the [1], who conducted a study on the potential impact of agricultural technology adoption on poverty alleviation strategies and found a positive effect of agricultural technology adoption on farm household wellbeing suggesting that there is a large scope for enhancing the role of agricultural technology in contributing to poverty alleviation. In this study, the impact of adoption of chemical fertilizer by farm households in Sibu sire Woreda will be analyzed through causal effect of average yield (output) between adopters and non-adopters using propensity score match. Any farm household using any amount of chemical fertilizer on his/her farmland will be considered as an adopter of chemical fertilizer, irrespective of the proportion of the chemical fertilizer covered by his/her farm land.

Impact is calculated by average treatment effect or ATT average treatment effect for the treated and in this study 'D' represent adoption which is a dummy variable such that D = 1 if the individual in the group adopt chemical fertilizer and D =0 otherwise. Let Y_1 - denote potential observed average yield for adopter; Y_0 - Potential yield for non-adopter. Then ATT, which is in this case, $Y = Y_1 - Y_0$ is the impact of chemical fertilizer on the individual in the treated group, $Y = DY_1 + (1 - D)Y_0$, is used to compute the treatment effect for every unit. The primary treatment effect of interest that can be estimated is therefore the Average impact of Treatment on the Treated (ATT). The value of welfare, Y_1 when the household is an adopter (D= 1) and Y_0 the same variable when it does not adopt chemical fertilizer; (D = 0). Then the observed welfare above is:

$$Y = \mathrm{DY1} + (1)\mathrm{Y0} \quad \text{.......... (7)}$$

When (D = 1) Y_1 is observed; when (D = 0) Y_0 is observed.

$\mathrm{ATT} = \mathrm{E}(\mathrm{Y}_1 - \mathrm{Y}_0|\mathrm{D} = 1) = \mathrm{E}(\mathrm{Y}_1|\mathrm{D} = 1) - \mathrm{E}(\mathrm{Y}_0|\mathrm{D} = 1)$...………… (8)

Only outcome variable of adopters is observed and the E (Y_1 | D = 1); however, it is not possible to observe the outcome of those adopters had they not adopted E (Y_0 | D = 1). Therefore, matching estimation assumes counterfactual analysis by matching treatment (Adoption) and control (Non adoption) as if they are similar groups. The primary assumption underlying matching estimators is the conditional independence assumption (CIA). The CIA states that the decision to participate is random conditional on observed covariates X [39] i.e. self-selective. This assumption implies that the counterfactual welfare indicators in the treated group are the same as the observed welfare growth indicators for the non-treated group:

$E(Y_0|X, D = 1 = E(Y_0|X, D = 0) = (Y_0|X)$.
………..…………...…. (9)

This assumption rules out adoption on the basis of unobservable gains from adoption. The CIA requires that the set of $X's$ should contain all the variables that jointly influence the welfare indicators with no treatment as well as the selection into treatment. Under the CIA, ATT can be computed as follows:

$ATT = E(Y_1 - Y_0|X, D = 1) = E(Y_1|X, D = 1) - E(Y_0|X, D = 1)$…..… (10)

Where $Y_1$is the treated outcome (farm yield of the adopters in this case), Y_0 is the untreated outcome (that of non-adopters), and D indicates the treatment status and is equal to 1 if the individual receives treatment and 0 otherwise. ATT calculated above is the difference between two terms with the first term being the welfare indicator (in this case farm yield) for the treated group (adopters of chemical fertilizer) which is observable and the second term being the welfare indicator for the treated group had it not been treated, representing a counterfactual situation which is unobservable and needs to be treated, the control group.

Sensitivity test

In observational studies, treatments are not randomly assigned to experimental units, so that randomization tests and their associated interval estimates are not generally applicable. In an effort to compensate for the lack of randomization, treated and control units are often matched on the basis of observed covariates; however, the possibility remains of bias due to residual imbalances in unobserved covariates.

To confirm the robustness of the finding of the ATT; the post estimation analysis of sensitivity test was checked. Sensitivity analysis examines how strong the influence of γ (unobserved) on the participation process needs to be. If there are unobserved variables that affect assignment in to treatment and the outcome variable simultaneously a hidden bias might arise to which matching estimators are not robust [40]. In participation probability given by:

$Pi = P(xi, ui) = P(Di = 1|xi, ui) = F(\beta xi + \gamma ui)$………........…...……
(11)

Where xi are the observed characteristics for individual i, u_i is the unobserved variables and γ is the effect of u_i on the participation decision. If the analysis is free of hidden bias γ is zero and the participation probability will be fixed only by xi. In case of hidden bias both group with the same observed covariates x has different chances of receiving treatment. Selectivity test evaluates how program effect is affected by change in γ. The following bounds on the odds ratio of the participation probability of both individuals are applied.

$\frac{1}{e^r} \leq \frac{pi(1-pj)}{pj(1-pi)} \leq e^r$………..................................…………….........…..............................…………..
(12)

Both individuals have the same probability of participation if e^r=1. e^r is a measure of degree of departure from a study that is free of hidden bias, [40], This chapter intended to the analysis and discussion of the data obtained in line with the objectives of the paper. The data gathered were investigated in detail to achieve the intended targets. Thus, both analysis methods; descriptive and econometric analysis were employed sequentially in this chapter.

Hypotheses and justification of explanatory variables

One of the crucial points in this section is to specify and hypothesize the dependent and independent variables that were used in the model. Regarding to its definition, measurement and hypotheses of variables (Table 2).

Table 2. List of explanatory variables used for the analysis.

Definition of Variable	Nature of Variable	Variable Definition and Measurement	Expected Sign
Age of the household head	Continuous	In year	-/+
Sex of household head	Dummy	If available =1, 0 otherwise)	+
Marital status	Dummy	If married = 1,0 Otherwise	-
Family size of household head	Continuous	Number of family members	-
Educational status	Dummy	If 1 literate, 0 otherwise	+
Labor available in the family	Continuous	In number	+
Livestock owned	Continuous	TLU	+
Membership of cooperative	Dummy	If member Yes=1,0 Otherwise	+
Access to extension	Dummy	If have access Yes = 1,0 otherwise	+
Distance to extension agent's office	Continuous	In working minutes	-
Access to credit	Dummy	If having access=1,0 otherwise	+
Access to information	Dummy	If having inf. = 1, 0 otherwise	+
Distance to nearest market	Continuous	In working minutes	-
Distance to nearest road	Continuous	In working minutes	-
Participation in nonfarm activity	Dummy	If have =1,0 otherwise	-/+

3. Results and Discussion

Out of total sample of 382 smallholder cereal crop farm household, 287 (75.13%) participated in adoption of chemical fertilizer in their cultivation of cereal crop, while the remaining 95 (24.87%) were no participating chemical fertilizer technology.

Table 3. Description of continuous variables.

Variables	Adopter (N = 287)			Non- adopter (N = 95)			Total (N = 382)			t value
	Mean	Min.	Max.	Mean	Min.	Max.	Mean	Min.	Max.	
Agehh	51.25	24	86	49.45	27	83	49.82	26	86	0.0825
Fshh	6	2	10	7.86	3	14	7.32	2	14	0.6320
Alhh	4.33	1	9	3.16	1	8	4.01	1	9	1.9815**
Lohh	3.65	1	5.5	2.35	0.5	5	2.75	0.5	5.5	3.4525***
Dea	2.25	0.5	4	2.75	1	4.5	2.54	0.5	4.5	0.1243
Dmhh	9.12	5	14	9.87	6	14	9.42	5	14	0.7822
Drhh	3.52	1	8	4.25	1.32	10	3.82	1	10	2.3472***

***, ** and * imply statistically significant at 1, 5 and 10% respectively

Table 3 illustrate the mean, minimum and maximum age of the smallholder head farmers, family size of household head, labor available in the family, livestock ownership, distance to extension agent's office, distance to market center and distance to road center of chemical fertilizer participant and non- participant in comparison. The descriptive statistics result for continuous variable (Table 3, t-value) reveal that there was no statistically significant difference between chemical fertilizer participant and non- participant concerning age of the smallholder head farmers, family size of household head, distance to extension agent's office and distance to market center while there was significant difference in availability of labor force, livestock ownership and distance to road center. This implies that availability of labor force, livestock ownership and distance to road center were crucial to smallholder head farmers to adopt or not to adopt chemical fertilizer of productive technology.

As shown in the (Table 4) summarizes frequency, percentage and level of determine of dummy variable. Accordingly, there was statistically significant difference between fertilizer participant and non- participant in education level of head, membership to cooperative, access to extension, access to credit and access to information. On the other hand, the difference between chemical fertilizer participant and non- participant is not significant in sex of household head, marital status and participation in nonfarm activity.

Table 4. Description of dummy variables.

Variables		Adopter (N = 287)		Non- adopter (N = 95)		t – value
		Frequency	Percent	Frequency	Percent	
Sexhh	Yes	225	73.39	72	75.79	
	No	62	26.61	23	24.21	0.3247
Mshh	Yes	234	81.53	47	49.47	
	No	54	18.47	48	50.53	0.7982
Eduhh	Yes	191	66.55	56	58.95	
	No	96	33.45	39	41.05	4.8746***
Mchh	Yes	98	34.15	14	14.74	
	No	189	65.85	81	85.26	3.2783***
Aehh	Yes	262	91.23	81	85.26	
	No	25	8.77	14	14.74	4.9986***
Achh	Yes	103	35.88	12	12.63	
	No	184	64.12	83	87.37	5.9784***
Aihh	Yes	96	33.45	4	4.21	
	No	191	66.55	91	95.79	3.2256
Pnfhh	Yes	187	65.16	17	17.89	
	No	100	34.84	78	82.11	0.4725

***, ** and * imply statistically significant at 1%, 5% and 10% respectively

According to (Table 5), about 48.43% of the sample smallholder farmers used improved variety cereal crop seed, 19.63% of sample smallholder farmers used local cereal crop seed and 31.94% of sample smallholder farmers used both. When we compare adopters 49.13% with non-adopters 46.31% using improved variety of cereal crop seed. According to the survey about 14.98% adopters and 33.68 % non-adopters used local cereal crop seed. Adopters 35.89% with non-adopters 20.01% used local and improved variety of cereal crop seed.

Table 5. Used cereal crop seeds by sample smallholder farmer's head.

Description of cereal crop seeds	Non adopters	Percent	Adopters	Percent	Sample households	Percent
Local cereal crop	32	33.68	43	14.98	75	19.63
Improved variety cereal crop	44	46.31	141	49.13	185	48.43
Both	19	20.01	103	35.89	122	31.94
Total	95	100	287	100	382	100

People have different attitude to do a certain task depending on their historical background, need for change; and social, economic and political environments. Program adopter households were also having different motives to practice the chemical fertilizer technology adoption decision program and even to select from the options available. Most adopters were, 95% of the households were adopting in the programs because of the awareness creation activities carried out by the Soro district Officials, Agriculture and Rural Development officers and Development agents. About 5% of the smallholder farmers were also joined chemical fertilizer technology adoption because of the initiation and pressure created by their family members and neighbors. As adopters responds chemical fertilizer technology of cereal crop helped them to increase productivity and income of cereal crop. The non-adopter smallholder farmers were forward different reasons for not adopting in the chemical fertilizer technology of cereal crop. The reasons for 10% respondents were lack of personal interest to adopt in chemical fertilizer technology of cereal crop, 38% respondents said our cultivated land is not suitable for chemical fertilizer technology of cereal crop due to logging water, hence we don`t have confidence to sow the available land we have in chemical fertilizer technology and 52% respondents said we don`t have enough labor force, not suitable sowing and takes time. In finally they said that as much as possible government should support farmers by distributing chemical fertilizer technology of cereal crop machine to substitute labor force and to decrease time expense.

Heckman two stage model analyses is employed to identify the smallholder farmers level demographic, socio-economic and institutional factors that influence the decision of smallholder farmer's chemical fertilizer technology adoption in the first stage by employing probit regression. In the second stage OLS method was applied to assess factors that determine the level of their adoption. In the study both multicollinearity and heteroscedasticity of continuous and discrete explanatory variables in the model were needed to be checked. The values of VIF approach to infinitive there is problem of multicollinearity, while VIF is below 10 there is no much problem. In this study all the value of VIF for continuous and discrete explanatory variables was blow 5. Therefore, there is no of multicollinearity problem. Breusch-Pagan test were applied to test the data for heteroscedasticity. The Breusch-Pagan test evaluates the null hypothesis of a constant variance in the data. Accordingly, Chi-square value results of STATA output the null hypothesis of a constant variance was not rejected implying absence of heteroscedasticity in survey data.

According to probit regression results (Table 6) revealed that the probit regression and marginal effect of probit finding of factors that determine the likelihood of smallholder cereal crop farmers' chemical fertilizer technology adoption decision. The models constructed with 15 explanatory variables and out of these 10 explanatory variables are significantly influencing the adoption decision with expected sign. These variables include size of family, education status of household head, availability of family labor force, livestock holding, accessibility of credit service, accessibility of extension service, access to chemical fertilizer technology information, distance to near market, distance near to road and participation of non-farm activity were significantly influence the smallholder cereal crop farmers' chemical fertilizer technology adoption decision. Whereas, age of household head; marital status; sex of household head; membership to farm cooperative and distance to extension agent office were insignificantly determine chemical fertilizer technology adoption decision but all variables with hypothesized sign determine the chemical fertilizer technology adoption decision.

Table 6. Factors that determine chemical fertilizer technology adoption decision Probit Model result.

Variables	Robust Coef.	Std. Err.	Odds Ratio	Z-value	P>│z│	dF/dx
Agehh	-1 .0037509	1.03853	0.9985046	-0.40	0.709	-0.0037509
Sexhh	0.645543	0.4672163	1.807583	1.57	0.254	0.2430854
Mshh	-1.2754043	1.6403102	0.5683160	-0.41	0.506	-0.0838025
Fshh	-1.2384221	0.1402197	1.9838723	-2.32	0.002	-0.1827992***
Eduhh	0.3353197	0.9281746	1.4263137	2.87	0.007	0.1481053***
Alhh	0.2037180	0.1085512	2.7586023	1.98	0.001	0.3657035***
Lohh	0.3711719	0.2250681	1.8482102	2.05	0.026	0.0941832**
Mchh	0.8781871	0.2700621	2.3721284	2.24	0.530	0.1310015
Aehh	1.0049263	0.9894562	1.9478530	2.03	0.045	0.2307639**
Dea	-1.8133917	1.0343842	1.8452794	-1.75	0.482	-0.9856721
Achh	0.5803870	0.3073143	1.8836082	1.62	0.076	0.1708203*
Aihh	0.8268131	1.4652873	2.4435621	2.30	0.052	0.1201015*
Dmhh	-0.0902171	0.2365746	0.8886070	-1.87	0.037	-0.1400701**
Drhh	-2.642065	1.5506206	1.8953821	-2.54	0.003	-0.2580404***
Pnfhh	1.7002560	1.5324879	2.1152483	1.71	0.058	0.2862779**
Cons.	1.7785235	1.0988421	0. 1411181	1.05	-	-

Number of observations = 382; LR chi2 (15) = 84.45; Probability > chi2 = 0.0000; Log likelihood = -97.47; Pseudo R2 = 0.5028; ***, ** and * imply statistically significant at 1, 5 and 10% respectively

According to Probit Regression Model results that the size of family, education status of household head, availability of family labor force, and distance near to road are significantly affecting the likelihood of program adoption at 1% level of probability, while livestock holding, accessibility of extension service, distance to near market and participation of non-farm activity are significantly affecting the likelihood of program adoption at 5% level of probability, while accessibility of credit service and access to chemical fertilizer technology information are significant at 10% level. Among the variables such as: education status of household head, availability of family labor force, livestock holding, accessibility of credit service, accessibility of extension service, access to chemical fertilizer technology information and participation of non-farm activity influence the likelihood of adoption of chemical fertilizer technology in the program positively as expected whereas the remaining variables such as: size of family, distance to near market and distance near to road have negative effect on chemical fertilizer technology adoption decision. The Pseudo R^2 which enlightens how well the repressors explain the adoption probability is 0.5028 as shown on the (table 6).

The family size of smallholder cereal crop farmers was negatively influence chemical fertilizer technology input and statistically significant at 1% level on the adoption of chemical fertilizer input. The marginal effect result reveals that smallholder cereal crop farmers, who have 1 additional ha of arable land, would decrease the likelihood of smallholder cereal crop farmers' chemical fertilizer adoption by 18.27 %. This finding is similar with [41]. Distance to the nearest road expected negative influence and is significant at 1% level, on the probability of adoption of chemical fertilizer in smallholder cereal crop farmer's production. Keeping other variables constant, compared with smallholder cereal crop farmers who have good access to roads on the spot, those smallholder cereal crop farmers who have no accessible road infrastructure reduce the probability of chemical fertilizer adoption of cereal crop by 25.8 %. As expected, distance to the nearest market was found to be negatively influenced the probability of participation of chemical fertilizer adoption decision at

5% significance level. Being all other things constant, 1-kilometer increase in a distance to near market, decreases participation of chemical fertilizer technology by 14%. This result is in line with the results of [42 – 44].

As hypothesized, the availability of family labor force has positively influenced the likelihood of smallholder cereal crop farmers' chemical fertilizer technology adoption decision and statistically significant 1% level. The marginal effect shows that the availability of 1 more active person in family increase the probability of chemical fertilizer input adoption on smallholder cereal crop cultivation by 36.57 %, holding all other determinants being constant. This finding is similar with the finding of [45]. Education level of household head was found to be positively influenced the probability of participation of chemical fertilizer technology in smallholder cereal crop cultivation. This variable was statistically significant at 1% level. Holding other variables constant, as compared to illiterate smallholder cereal crop farmers the probability of participation of chemical fertilizer technology in smallholder cereal crop production for literate smallholder cereal crop farmers would increase by 14.81%. This is similar with the studies of [24, 46]. Access to chemical fertilizer input market information has shown positive influence on likelihood of smallholder cereal crop farmers' chemical fertilizer technology adoption decision at 10% level of significance. Keeping other variables constant, smallholder cereal crop farmers with accessibility to input market information have 12% better opportunity to adopt chemical fertilizer technology than those with insufficiency of information about chemical fertilizer cereal crop technology.

As expected, access to extension influences smallholder cereal crop farmer's chemical fertilizer technology adoption positively and statistically significant at 5% level of significance. Keeping other variables fixed, availability of extension services encourages the likelihood of smallholder cereal crop farmer's chemical fertilizer technology adoption decision by 23%. Participation of off farm activities determines chemical fertilizer technology adoption positively and statistically significant at 10% level. Keeping other things constant, participation in off farm activities increase smallholder cereal crop farmers' chemical fertilizer technology adoption decision by 28.63% than those not participated on off farm activities. Access to credit service determines smallholder cereal crop farmer's chemical fertilizer technology adoption positively and statistically significant at 10% level of significance. Keeping other variables fixed, availability of credit service increases the likelihood of smallholder cereal crop farmer's chemical fertilizer technology adoption decision by 17%. This result was similar with finding of [47]. As hypothesized, livestock holding influences smallholder cereal crop farmer's chemical fertilizer technology adoption positively and statistically significant at 5% level of significance. Keeping other variables fixed, increase livestock holding by 1 TLU, increases the likelihood of smallholder cereal crop farmer's chemical fertilizer technology adoption decision by 9.42%.

The Heckman model in the second stage determination assesses the factors that influence the intensity of chemical fertilizer participated using the OLS model. The coefficient of inverse λ is statistically significant at 1% level. λ identified as statistically significant determinant factors of adoption may or may not be statistically significant determinant factors on the output model of intensity. (Table 7) shows that the Heckman model regression results of determinants that affect the level of chemical fertilizer technology adoption among smallholder cereal crop farmers. Out of 16 independent variables such as: sex of household head, size of family member, the number of family labor force, educational status of house hold head, marital status, membership to cooperative, availability of extension service, access to credit, livestock holding and lambda significantly determine the intensity of chemical fertilizer technology adoption, while age of house hold head, the existing road condition, availability of input information and distance to the nearest market place insignificant to determine the level of adoption.

Table 7. Results of the second-stage selection estimation (intensification of technology adoption).

Variables	**Robust Coef.**	**Std. Err.**	**t**	**P>│z│**
Age of the household head	0.0654688	0.0758335	1.78	0.709
Sex of household head	- 0.8324279***	2.9637705	-3.74	0.003
Marital status	-0.0382338	0.1427354	1.52	0.004
Family size of household head	-4.2619283*	3.8994324	-2.62	0.062
Educational status	3.1834261***	3.5107432	2.45	0.001
Labor available in the family	0.5464822***	0.925544	2.38	0.004
Livestock owned	2.2984632**	2.4532576	2.93	0.012
Membership of cooperative	1.5379031*	1.0542517	2.13	0.054
Access to extension	3.8233479***	2.1482472	1.96	0.002
Distance to extension agents	-2.4328608	1.9728137	-1.89	0.674
Access to credit	2.1972986***	1.2462314	1.97	0.007
Access to information	0.1824545	1.2399784	1.30	0.475
Distance to nearest market	-1.2378152	1.2482665	-1.53	0.540
Distance to nearest road	-2.8352761	1.8734528	-1.54	0.783
Participation in nonfarm activity	-2.4237928	2.3423974	-1.87	0.005
Mills lambda (λ)	1.6430581***	1.2582746	1.92	0.005
Constant	1.2475336***	0.1897312	1.25	0.002

Number of observations = 382; Adopter = 287; Non adopter= 95; R-squared = 0.5435; Adj. R-squared = 0.7672; ***, ** and * imply statistically significant at 1, 5 and 10% respectively

Similar to the first stage result, size of family member, education status of household head, availability of family labor force, livestock holding, accessibility of credit service and accessibility of extension service influence both participation decision and intensity of participation significantly with expected sing. Moreover, Sex of household, education status, availability of family labor force, accessibility of credit service and accessibility of extension service have statistically significant and determine chemical fertilizer adoption at 1% significant level. Livestock owned is also shown expected sign and statistically significant at 5% level. Membership of cooperative and family size determines chemical fertilizer adoption statistically at 10% significant level. Regarding to determinant variables, age of head, marital status, distance to extension agent's office, agricultural technology information, distance to market and road, and participation in nonfarm activity were statistically insignificant to influence the intensity of chemical fertilizer technology adoption decision.

Propensity score matching algorithm can be selected based on its own criteria: balancing test, Pseudo R-square (low), matched sample size (large) and LR chi-square (insignificant), the algorithm which are selected from four matching algorithms: nearest neighbor matching (NNM), radius matching (RM), caliper matching (CM), and kernel matching (KM). Accordingly, nearest neighbor matching method 4 was found to be the best estimator, since it resulted in the least pseudo R-square (0.027), had insignificant LR chi-square (LR = 4.59, p = 0.884) and large matched sample size (380) by discarding 2 unmatched smallholder farmers from chemical fertilizer adopter of total of 382 smallholder farmers.

Table 8. Selection of matching algorithm.

Matching Algorithm		**Before matching**			**After matching**		
		Pseudo R2	**LR Chi2**	**P - value**	**Pseudo R2**	**LR Chi2**	**P – value**
NN	(1)	0.255	87.37	0.000	0.047	8.84	0.846
	(2)	0.255	87.37	0.000	0.036	6.65	0.776
	(3)	0.255	87.37	0.000	0.039	7.23	0.812
	(4)	0.255	87.37	0.000	0.027	4.59	0.884
	(5)	0.255	87.37	0.000	0.039	7.07	0.710
KM	(0.1)	0.255	87.37	0.000	0.038	6.95	0.727
	(0.25)	0.255	87.37	0.000	0.039	7.30	0.262
	(0.5)	0.255	87.37	0.000	0.073	24.63	0.024
RM	(0.01)	0.255	87.37	0.000	0.448	61.77	0.000
	(0.1)	0.255	87.37	0.000	0.448	61.77	0.000
	(0.25)	0.255	87.37	0.000	0.448	61.77	0.000
Caliper	(0.1)	0.255	87.37	0.000	0.047	8.83	0.846
	(0.25)	0.255	87.37	0.000	0.047	8.83	0.846
	(0.5)	0.255	87.37	0.000	0.047	8.83	0.846

The necessary steps when implementing propensity score matching Model are: propensity score estimation, choose matching algorithm, Check overlap/common support. Matching of participant and non- participant smallholder farmers were carried out to determine the common support region. The basic criterion for determining the common support region is to delete all observations whose propensity score is smaller than the minimum propensity scores of participants and larger than the maximum in the control group [48]. That is, deleting all observations out of the overlapping region. The summary statistics of propensity scores of farmers (Table 9), the predicted propensity scores for adopters and non-adopters of chemical fertilizer technology of smallholder farmer range from 0.0456776 to 0.09601382 with mean value of 0.750686 and standard deviation 0.3602327 for the adopter farmers, while it ranges from 0.038271 to 0.968723 with mean value of 0.3609523 and standard deviation 0.3309726 for those non-adopter farmers. The common support region indicates that the propensity score for the overlap region ranges from 0.0456776 to 0.968723. Therefore, the production impact analysis considered both smallholder farmers involved in adopters and non-adopters of chemical fertilizer technology with propensity score of the overlap region i.e. propensity score ranging from 0.0456776 to 0.968723. Accordingly, the common support region was satisfied in the range of 0.0456776 to 0.968723by deleting 2 observations from those adopters.

Table 9. Predict propensity score common support region.

Observations	**Mean**	**Std. Dev.**	**Min.**	**Max.**
Non adopter	0.3609523	0.3309726	0.03827	0.968723
Adopter	0.750686	0.3602367	0.0456776	0.9601382
Total	0.5376834	0.4078088	0.38272	0.9601382

Table 10 reports the estimated treatment effects from the propensity score matching. Results revealed that chemical fertilizer technology had significant effect on household food security as evidenced by the significantly higher per capita consumption expenditure which is key indicators of food security, annual income and yield resulting from adoption ($p < 0.01$).

Table 10. Predict propensity score common support region.

Outcome	Treated	Controls	Difference	BSE	T-stat
Cereal crop yield (Qt/ha (year))	24.75	6.25	18.50	0.89	3.52***
Annual cereal crop income (Birr)	25927.92	9354.52	16573.40	12324.54	3.50***
Food Consumption per capita (Birr)	24325.74	10125.75	14199.99	12745.78	5.50***

*** P < 0.01

Food consumption expenditure of adopting chemical fertilizer technology of smallholder farmers was much higher than those who didn't adopt chemical fertilizer technology on average by 14,199.99 Birr. Given the mean level of consumption per capita in the study area, which is hardly in excess of half the average treatment effect reported implying that the estimated effect associated with adoption chemical fertilizer technology is quite large. Similarly, the income of participants of chemical fertilizer technology was also found to be significantly higher than those of their non-participant's counterparts by 16,573.40 Birr on overage in given product year. On the other hand, the results also showed that chemical fertilizer technology had significant effect on Cereal crop yield at 1% significance level ($p < 0.01$) during the 2018/19 cropping season. The average yields of cereal crop of participant smallholder farmers were higher by 18.50 quintals/ha when compared with the average cereal yields of non- participant smallholder farmers. This is quite a substantial cereal crop yield enhancement considering the mean cereal crop yield in the study area. These findings indicate that participation of chemical fertilizer technology had indeed a significant positive impact on smallholder farmer's food security. In particular, participation was associated with significantly higher food consumption expenditure per capita, enhanced net annual income, higher cereal crop yield and enhanced spending on farm inputs. Hence, participation of chemical fertilizer technology of cereal crop had a positive impact on the life of the participants indicating positive food security effect or reduction of poverty level on the side of the participants.

Sensitivity analysis is a strong identifying assumption and must be justified. According to [49] sensitivity analysis is the final diagnostic that must be performed to check the sensitivity of the estimated treatment effect to small changes in the specification of the propensity score. In (table 11) result was reported that based on this concept of the sensitivity analysis shows that the significance level is unaffected even if the gamma values are relaxed in any desirable level even up to 100%. This shows that average treatment effect on treated is not sensitive to external change. Hence there are no external variables which affect the result above calculated for ATT result.

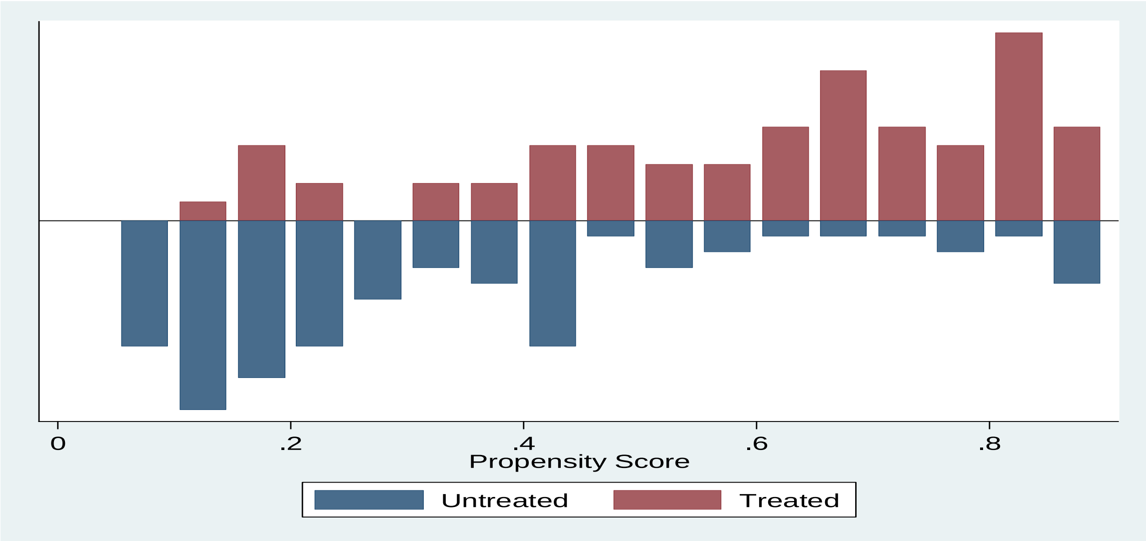
Table 11. Sensitivity test of external effect on ATT.

Gamma	Q-mh+	Q-mh-	P-mh+	P-mh-
1	11.7071	11.7071	0	0
1.05	11.604	11.8948	0	0
1.5	10.5988	13.0192	0	0
2	9.8498	14.8128	0	0
2.5	9.30418	15.5101	0	0
3	8.87996	16.1248	0	0
3.5	8.53572	16.6767	$1.1e^{-16}$	0
4	8.2478	17.1790	$6.7e^{-16}$	0
4.5	8.00148	17.6410	$3.4e^{-15}$	0

Gamma: odds of differential assignment due to unobserved factors; Q-mh+: Mantel-Haenszel statistic (assumption: overestimation of treatment effect); Q-mh-: Mantel-Haenszel statistic (assumption:

underestimation of treatment effect); P-mh+: significance level (assumption: overestimation of treatment effect); P-mh-: significance level (assumption: underestimation of treatment effect)

Figure 1. Propensity score matching distribution of matched sample.



4. Conclusions

This study conducted to investigate the determinants of adopting chemical fertilizer technology of cereal crop, intensity of employing and its impact on smallholder farmer's food security in the study area. To this end, this study was employed with the aim of investigating the institutional, demographic and socioeconomic factors that influence the adoption decision of chemical fertilizer technology and extent of chemical fertilizer among smallholder cereal crop farmers, and its impact on smallholder farmer's food security. Descriptive and econometrics analysis such as: Heckman two stage and propensity score matching models were developed to analysis the cross-sectional survey data. The study applied cross sectional smallholder farmer level data collected in 2019 cropping season from 382 samples of smallholder farmers. Propensity score matching model was used to compare participant smallholder farmers with non- participant smallholder farmers in terms of three key measure of smallholder farmers' yield of cereal crop, consumption expenditure and annual income. The matching techniques conducted were the NNM, KM, RM and CM. Among the algorithms used NNM (4) was found to be the best estimator of data based on balancing test, pseudo R^2 and sample size. The results showed that chemical fertilizer of cereal crop technology had significantly positive impact on farmers' cereal crop yields, food consumption expenditure and income. The average treatment effect on the treated (ATT) was 16,573.40 Ethiopian Birr net income, 14,199.99 Ethiopian Birr net food consumption expenditure and about 13.50 quintals yield/ha increase for participants as compared to non- participants. The significance of coefficient of inverse λ reveals that the presence of selection bias and the effectiveness of employing Heckman two stage model. The main factors affecting adoption decision of chemical fertilizer cereal crop technology are the size of family, education status of household head, availability of family labor force, livestock holding, accessibility of credit service, accessibility of extension service, access to chemical fertilizer technology information, distance to near market, distance near to road and participation of non-farm. Whereas intensity of chemical fertilizer application decission influenced by sex of household head, size of family member, the number of family labor force, educational status of house hold head, marital status, membership to cooperative, availability of extension service, access to credit, livestock holding and lambda.

Given these findings, a number of implications could emerge from analysis up on which important suggestions could be made as key recommendations. Improved chemical fertilizer technology involves the use of different practices, which require knowledge and skill of application. Education was found to have a strong relation with the chemical fertilizer technology as it enhances cereal crop yields, household income and food consumption expenditure. Therefore, due emphasis has to be given towards strengthening smallholder rural farmers education at different levels using FTC. Increasing the number of cooperative organizations in the rural area in which the smallholder farmers will be able to get credit is basis in enhancing the adoption of chemical fertilizer technology. Further, it is apparent from the study that if smallholder farmers get credit more easily, they would use chemical fertilizer technology to enhance cereal crop yields, household income and food consumption expenditure. Thus, the credit facility should target poor smallholder farmers especially those who were not adopting the chemical fertilizer technology due to lack of operating capital. This may encourage the smallholder farmers to do commercial farming practice in which they can build their asset to implement the adoption of chemical fertilizer technology on their farms. The agricultural extension activities need to consider additional modern agronomic practices. Extension services crucial activities in agricultural sector to improve adoption of chemical fertilizer technology, through which induce farm cereal crop yields, household income and food consumption expenditure. A significant proportion of farmers had no formal education; the extension program should be targeted to the less educated farmers for its effective delivery through special training, seminars, field demonstrations, and technical support should be facilitated to enhance the adoption rate of chemical fertilizer technology. The extension should contact farmers individually as well as in group to be awarded in terms of cereal crop chemical fertilizer technology is suitable to improve household food security. Moreover, the policies which expand the accessibility to increasing livestock holding for smallholder farmers have potential to increase and strengthen of chemical fertilizer technology adoption decision. Hence, expansion in the level of adoption of chemical fertilizer technology would consequently result in substantial on household cereal crop yields, household income and food consumption expenditure on a sustainable basis.

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