Adoption of Chemical Fertilizer Technology and Household Food Security in Southern Ethiopia

Negese TAMIRAT MULATU (✉)

Summary

The adoption of chemical fertilizer technologies is crucial for sustainable economic development. The relation of chemical fertilizer technology adoption decision and food security of agricultural sector has been poorly understood. Therefore, this study attempts to investigate the factors affecting adoption decisions and their impact on food security in southern Ethiopia using cross-sectional survey data gathered in 2019/20. A field survey was collected among 382 smallholder farmers in the Soro district. Descriptive statistics and econometric methods such as probit regression, Heckman two stage-method, and propensity score matching were employed for the data analysis. The results of probit regression showed that the technology participant was significantly affected by education status, size of family, family labor, livestock holding, credit service, extension service, agricultural technology information, distance to market, distance to road, and non-farm activity. Adoption was associated with a significantly higher crop yield and expenditure. The findings suggest that the role of technology adoption at the farm level due to higher yield and income could lead to reduced poverty. The results suggest that the role of chemical fertilizer technology adoption in improving household food security among smallholder farmers results mainly in higher cereal crop yields and incomes.

Key words

chemical fertilizer, food security, Heckman two stages method; intensity; propensity score matching

Department of Economics, College of Business and Economics, Jimma University, P. O. Box: 387, Ethiopia

✉ Corresponding author: negesefb@gmail.com

Received: January 14, 2021 | Accepted: April 26, 2021

Introduction

Agriculture is a crucial sector in the economic policy of many developing countries. The sector plays center stage in alleviating food insecurity and poverty in both developed and developing countries (Becerril and Abdulai, 2009; Mendola, 2007). Poverty alleviation can mainly be achieved by agricultural growth. The agricultural sector is the development means for enhancing Millennium Development Goals by 2015, despite the fact that the sector creates spillover effects to the industrial, service, and tourism sectors (World Bank, 2014) This is due to the low adoption of chemical fertilizer technology and techniques. Agricultural technology can be described as the integration of knowledge and means of creating a new environment and decision to make full application of innovation to improve people's lives (Rogers, 2003). Rural poverty increases due to low attention given to the utilization of chemical fertilizer (Uaiene et al., 2009). However, the majority of rural area farmers depend on traditional methods of production with low yields because these farmers have very poor knowledge of chemical fertilizer utilization. According to the study of (Ibrahim et al., 2012), results revealed that the adoption of agricultural technology enhanced income resulting from higher cereal crop yields.

Agriculture is by far the largest sector of Ethiopia's economy serving as a basis for reducing the country's food insecurity and source of livelihood for over 80% of its people. Technological change in agriculture holds increasing yield through the expansion of chemical fertilizer technology (CSA, 2017; Gebrerufael et al., 2015). The sector contributes 50% to the GDP, 90% of export earnings, 85% labor force, and 70% of raw materials in the countries. The agricultural sector showed a lower growth rate of 2.3% in 2015/16 (NBE, 2016). Several factors have been cited as responsible for such a low level of growth rate. Most of the nature of the agricultural sector is featured by subsistence and seasonal rain-fed, backward technology adoption decision, poor quality agricultural performance, income inequality, and massive population increment. Consequently, the country has had difficulties to meet its high demands for food security; thereby remaining net importers from other countries despite its huge potential for adoption decision and cereal crop yield (NBE, 2016).

The Ethiopian government formulated policies and strategies with high priority for the agricultural sector to accelerate agricultural growth and striving for agricultural productivity to achieve food security, poverty alleviation, and rural development (Yuko and Kei, 2012). Chemical fertilizer technology can contribute to increasing food production and to economy-wide growth as well. The sector has poorly performed in terms of yield for the past four decades (Beyene, 2011). According to (MoFED, 2010), the backwardness of the agricultural technology used is the major responsibility for the poor performance of the Ethiopian agricultural sector. Hence, the current Ethiopian government and policymakers strongly believe that the agricultural sector is a key transformation to overcome poverty and food security. Hence, the government has initiated agricultural expansion packages and extension programs to promote the adoption of farm-level chemical fertilizer technology (Samuel, 2006). In terms of utilization of annual chemical fertilizer 30% to 40% of rural smallholder farmers adopt on average 37kg/ha to 40kg/ha, which is below recommended 300kg/ha (MoA, 2012). Agricultural yield can be ensured by adopting chemical fertilizer technologies to meet the expected rising agricultural productivity demand. Advanced agricultural technology tends to increase agricultural gains (Challa, 2013). The adoption of chemical fertilizer technology enhances agricultural yield (Lavison, 2013; World Bank, 2008).

Understanding the factors underlying farmers' adoption decisions of agricultural technologies, such as chemical fertilizer technology, is crucial in terms of achieving enhanced crop yield through improved adoption of such technologies. There is a growing body of literature focusing on determinants of adoption decision and impact of farmers' choice of technological adoption (Bezabih, 2007; Kapalasa, 2014; Lelissa, 1998; Merga and Urgessa, 2014; Michael and Philip, 2007; Yuko and Kei, 2012), used Probit and Tobit models for institutional, economic and social variables in central Mid-hills of Nepal, Vihiga County in West Kenya, Tanzania and (West Shewa, Babile District, and West Wollega) of Ethiopia were significantly influencing rural area farmers' adoption and decision of chemical fertilizer technology. Their studies revealed that the age, level of education, access to extension services, access to farm inputs and output market, use of animal dung, land renting out, oxen ownership, value cost ratio, and several family sizes influenced rural area farmers' adoption decision and intensity of chemical fertilizer technology. (Bayissa, 2014; Holden and Lunduka, 2012; Kapalasa, 2014), using a panel and bivariate probit model of their studies found that variables like sex, age, educational level, farming experience, yield superiority, participation in crop production training, access to extension services nearest to market, the maturity period of new varieties and use of improved cereal crop varieties were significantly influencing 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 (Admassie and Ayele, 2010; Akpan et al., 2012; Hassen et al., 2012; Martey et al., 2014; Merga and Urgessa, 2014; Michael and Philip, 2007; Nigussie et al., 2012; Thuo et al., 2005). However, most of these studies were limited in dealing with identifying the factors affecting the adoption decision of the framers and their effect on crop yield. In low-income countries enhancing the food security of farmers depends highly on poor agricultural yields due to low agricultural technology adoption. An improved agricultural technology influences farmers' income and yields (Ajayi et al., 2003; Ibrahim et al., 2012). According to the study of (IFC, 2013), chemical fertilizer utilization in Egypt (50kg/ha) is higher than in Ethiopia, where it is near to zero. To this end, the current study has been conducted to investigate the effect of chemical fertilizer technology on cereal crop income, consumption expenditure, and cereal crop yield. Specifically, the objectives of the study were to investigate factors affecting chemical fertilizer technology adoption decisions in cereal cropping and evaluate its effect on household food security and production-related outcomes such as income, consumption expenditure, and crop yield in the study area.

Materials and methods

Description of the Study Area

This study was developed in Soro district. It is located in Hadiya Zone in southern Ethiopia lying between 7⁰23'00" and 7⁰46'00" north latitude and 37⁰18'00" and 37⁰23'00" east longitude. The district has an altitude that ranges from 840 – 2850 meters above sea level. Gimbichu, the capital of the district is about 260 km away from Addis Ababa and 32 km southwest from Hosanna. The district comprises 46 rural kebeles, 3 rural towns and has a total population of 229,617 of which 114,489 (48.86%) are male and 115,128 (50.18%) are female. The population density in the district is 222 per km^2 and the average landholding farm family is 0.4 ha and a total area of farms is 58,061 ha. According to SWADO reports for 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 is 1260mm and the average temperature is 190c. The district practice is mixed crop-livestock farming; thus, both cereal crop and livestock contribute their share to the farmers' agricultural income. Soro District is one of the main surplus grains producing area of the Hadiya Zone and wheat and teff is the main cash crop.

Sampling Technique

A multi-stage probability sampling method was employed to select the sample cereal crop grower. In the first stage: six cereal crop grower kebeles were randomly selected from cereal crop growing kebeles in the district, based on their agro-ecology: two of the kebeles (Shon kola and Kosha) from Dega kebeles, one of the kebele (Danetora) from Weina Dega kebeles and the three of the kebeles (Kecha, Bure, and Sundusa) from Kola kebeles. In the second and final stage: total numbers of cereal crop growers (3,696) were selected from a list of each selected cereal crop kebeles growers stratified by adoption status. A total sample size of 382 cereal crop growers was selected from each stratum using proportionate sampling procedures. Finally, the sample respondents from six kebeles would be selected randomly by employing randomly sampling methods. Sample cereal crop grower was formulated based on the econometric formula $n = [(Z^2p(1-p)]/e^2$ given by (Cochran, 1977). Accordingly, a total of 382 farm households were selected for the survey during the 2019/20 cereal cropping season.

Types and Sources of Data

Descriptive statistics and econometric methods were employed for the data analysis. Primary and secondary data were used. Qualitative and quantitative primary data were employed. In the primary data collection cereal crop grower demographic and socio-economic characteristics and adoption decision information were included. To get the required primary data questionnaires, key informant interviews and focus group discussion were used. To address the objectives of the study, open and close-ended questionnaires were prepared. The study was supplemented by secondary data obtained from published and unpublished documents, extension office, administrative office, relevant literature, website, and other relevant organizations. Information obtained from secondary sources included a list of rural cereal crop growers and non – growers. Furthermore, interviews were held with key informants. Cross-sectional field survey data was collected in the months between March and July 2019/20.

Data Analysis

Data analysis was carried out using descriptive statistics and econometric methods. Descriptive analysis examined demographic characteristics and socio-economic profiles of the cereal crop growers and performed using indicators such as frequency, averages, percentages, tables, standard deviation, maximum and minimum values, $\chi2$ and t-test. Specifically, I used $\chi2$ tests for evaluating associations between adoption status and qualitative factors.

Table 1. Sample of cereal crop grower based on the adoption status

Kebele	Total 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	1,613	165	2,083	217	382

Note: n_i= total sample from kebeles i (i = 1, 2, 3, 4); N_i= total households in kebeles 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

Furthermore, a t-test was used to check whether treated groups were different from control groups in terms of selected quantitative factors, thereby searching for potential relationships. Next, I applied econometric methods to provide a more appropriate and in-depth analysis. More specifically, I employed the probit model to explore factors affecting the adoption of chemical fertilizer technology among cereal crop-producing households and its efficiency (Gujarati, 2003). The Heckman two stage-model was developed to examine factors affecting the intensity of technology adoption (Greene, 2007; Heckman, 1979). Besides, the propensity score matching technique was employed to measure the effect of adoption of the technology (Winship and Mare, 1992; Heckman, Ichimura, and Todd, 1999; Mendola, 2007; Wooldridge, 2013).

According to the previous studies (Bayissa, 2014; Bezabih, 2007; Holden and Lunduka, 2012; Kapalasa, 2014; Merga and Urgessa, 2014; Michael and Philip, 2007; Yuko and Kei, 2012), developed research on chemical fertilizer technology showed how significant all of it was on the yield. This indicated that participants of chemical fertilizer technology enhanced yield more than their counterparts. Yield is the indicator variable for their studies, any change in yield brings a change in household wellbeing. The current study focuses on examining the effect of chemical fertilizer technology on smallholder farmer's food consumption expenditure which is a key indicator of food security and wellbeing. Adoption of chemical fertilizer technology, food security, and smallholder farmer's wellbeing are positively correlated. This reveals that any change in indicator variables such as cereal crop yield, annual income, and smallholder farmer's expenditure brings a change and is beneficial to the household. To examine factors influencing the adoption of chemical fertilizer technology among cereal crop-producing households, the model to be estimated will take the following form:

$$ADOPT_i = \alpha + \beta X_i + u_i \qquad (1)$$

where $ADOPT_i$ is the adoption status of household *i*, which takes score 1 for households which have adopted chemical fertilizer technology in cereal crop production and 0 otherwise.; X_i is a vector of covariates including socioeconomic, demographic and institutional factors that are presumed to affect adoption status of household *i* (Table 2); u_i is the error term of the model such that $u_i \sim N(0,\sigma^2)$; and α, β are model parameters to be determined. Given my dependent variable is dichotomous, the probit and logit models are commonly employed techniques to estimate the technical specification given by equation (1). In this study, the probit model is employed for the interpretation of the parameter estimates in probability terms. For investigating the effect of adoption of chemical fertilizer technology on household food security – the main interest of my analysis – I employed the following three food security outcome indicators at the household level: (i) cereal crop yield, measured by the total amount of cereal crop production at the household level expressed in quintals per hectare of land; (ii) total annual household income, expressed in Ethiopian Birr (ETB); (iii) total household food consumption expenditure, expressed in ETB. To assess whether adoption status is associated with differences in household-level food security outcomes, the following regression specification may be employed:

$$Y_i = \alpha + \gamma ADOPT_i + \beta X_i + \xi_i \qquad (2)$$

where Y is the measure of household food security; γ is the parameter of interest for estimating the effect of adoption; ξ is the model error term and the rest of the definitions are as in (1). A major methodological challenge associated with the estimation of the model (2) through the usual least-square procedure is that the parameter γ would typically be biased – a situation commonly referred to as 'self-selection' bias (Wooldridge, 2013). This is mainly because households' decision to adopt the chemical fertilizer technology is likely not random and such decisions could be systematically related to other factors that affect household food security outcomes. Besides, there are also unobservable differences between the two groups of households. The implication is that the two groups are not comparable and that any difference between the two in terms of food security cannot be attributed to differences in adoption status alone. Consequently, the measurement of impact based on γ fails to separate the effect of adoption (i.e., treatment effect) from that attributable to systematic differences (i.e., selection bias). To address this challenge, we employ propensity score matching combined with a sensitivity analysis that tests the assumption of selection on observables (Rosembaum and Rubin, 1983). The idea of propensity score matching is to show a comparison group that is based on a model of the probability of adopting in the treatment – also known as propensity score matching – using observed characteristics and then match participants to non-participants based on this probability of participating. The average treatment effect is then determined as the average difference in outcomes across these treated and control groups. The validity of propensity score matching depends on two important conditions: (i) conditional independence (i.e., the assumption that unobserved factors do not influence adoption); and (ii) a sizable common support or overlap region in propensity scores matching across the treatment and control groups.

The fulfillment of the propensity score matching conditional independence characteristics needs that give observable covariates, potential findings are not dependent on adopters' assignment. This entails that the assignment to adopter and control groups depends on observable variables, and this is a strong characteristic to make. The overlap propensity scores matching condition, on the other hand, checks that adopter respondents have comparison respondents nearby in the propensity score matching distribution. The effectiveness of propensity score matching also not independents on having a very large and roughly equal number of adopter and control respondents so that a basic region of overlap can be found.

Accordingly, I estimated the average treatment effect of adoption of cereal crop chemical fertilizer technology on all three outcome measures mentioned earlier. For this, I first estimated the propensity scores, using a probit model specified in equation (1). Only variables that are not possibly influenced by adoption status were included for the estimation. I then matched households using four of the matching algorithms: the nearest neighbor matching (NN), radius matching (RM), caliper matching (CM), and kernel matching (KM) (Caliendo and Kopeinig, 2008). I then estimated the average treatment effect as the average weighted difference in findings between adopters and matched non-adopters using bootstrapped standard errors. To ensure the validity of the common support, I used observations in the common support region only and deleted all other observations whose propensity score was lower than that of the minimum for treated and higher than that of the maximum for the controlled (Caliendo and Kopeinig, 2008).

Table 2. List of explanatory variables used for the analysis

Variable name	Variable type	Variable description and its measurement	Expected Sign
Age	Continuous	In year	-/+
Sex	Dummy	If 1 = available, 0 = otherwise)	+
Marital status	Dummy	If 1 = married, 0 = otherwise	-
Size of family	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 1 = Yes,0 = otherwise	+
Access to extension service	Dummy	If 1 = Yes, 0 = otherwise	+
Distance to extension agent's	Continuous	In working minutes	-
Access to credit service	Dummy	If 1 = Yes, 0 = otherwise	+
Access to information	Dummy	If 1 = Yes, 0 = otherwise	+
Distance to the nearest market	Continuous	In working minutes	-
Distance to the nearest road	Continuous	In working minutes	-
Adoption in nonfarm activity	Dummy	If 1 = Yes, 0 = otherwise	-/+

Source: Authors hypothesis 2019/20

To determine the best matching algorithm, I used performance criteria such as balancing test of covariate means on the matched samples using t-tests. Furthermore, I also tested the balancing properties by estimating the propensity score matching on the matched sample and performing a likelihood ratio test on the mutual significant effect of all regressors. Accordingly, lower Pseudo R^2 from the re-estimation of the propensity score and significance of the LR Chi2 test indicated fulfillment of the balancing properties.

Finally, to ensure the validity of the conditional independence assumption, I conducted a sensitivity analysis as a means of checking for the robustness of the results. The idea is to check whether unobserved factors affecting both the treatment and the measured outcomes thereby result in a 'hidden/selection bias'. This was accomplished by checking the degree to which the estimated adopters' effect is sensitive to lower changes in the formulation of the propensity score matching. To confirm the robustness of the finding of the average treatment effect on the treated, the post estimation analysis of sensitivity test was checked. Sensitivity analysis examines how strong the influences of γ (unobserved) on the participation process need to be. If there are unobserved variables that affect assignment is to treat and the outcome variable simultaneously a hidden bias might arise to which matching estimators are not robust. It evaluates how the program effect is affected by a change. If the analysis is free of hidden bias, γ is zero. This sensitivity analysis is in line with the sensitivity analysis of (Debelo, 2015).

Results and Discussion

Descriptive Analysis

Table 3 presents summary statistics of the cereal crop grower by type of chemical fertilizer technology (i.e., adoption status). About 287 (75.13%) of the total farm households practiced chemical fertilizer technology, which was relatively larger than those who didn't 95 (24.87%) during the 2019/20 cropping season.

Based on responses to open-ended questions put to respondents, lack of personal interest, un-suitability of cultivated land due to logging water, shortage of labor force, and the time-consuming nature of the chemical fertilizer technology were among the reasons cited for not practicing chemical fertilizer technology. Some of the respondents went to the extent of suggesting the need for government to consider distributing chemical fertilizer machines as a means to substitute for labor force deficits and shorten cereal crop planting time.

In Table 4, I present summary statistics (i.e., means and standard deviations) for the major explanatory variables by adoption status. Also reported are the t-test and chi-square comparisons of means of these variables across the two categories of farmers. Accordingly, in most of the sampled households that are relatively older (about 49.82 years of age), similarly, adopters had significantly smaller family size than non-adopters. The majority of the households are endowed with sufficient family labor, own cultivated 3.65 hectares of land on average.

Table 3. Sample farm households by adoption status

Chemical fertilizer technology adoption	Frequency	Percent	Cumm. percent
Practiced chemical fertilizer technology	287	75.13	75.13
Didn't practiced chemical fertilizer technology	95	24.87	100
Total	382	100	

Source: Own survey 2019/20

Table 4. Household characteristics (continuous variables) by adoption status

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***

Source: Computed from own survey data 2019/20; *t-values* for continuous explanatory variables; Figures in parentheses are standard errors. *** $P < 0.01$

Besides, adopters cultivate larger farmlands. Adopters are better in terms of distance to extension agents, markets, and road.

In Table 5, according to education, literate 64.65% farmers are literate, with attained primary level of education or above. Moreover, important differences were observed among adopters and non-adopters in terms of household characteristics. Accordingly, adopters had better-educated heads than those of non-adopters, suggesting that education might be positively correlated with adoption decisions. The two groups also significantly differed in terms of access to institutional services where adopters had better access to extension than their non-adopting counterparts but adopters were no better members of cooperatives and neither had better access to credit services. Lastly, there was no difference in terms of sex, marital status, utilization of information, and practice of non-farm activities. Any better change in the above-listed variable brings better change to adopters in cereal crop yield and annual income than to non-adopters.

Econometric Results

Model estimates for the determinants of household decisions to adopt the chemical fertilizer technology are presented in Table 6. The goodness fit concerning the predictive efficiency was high with 330 (86.34%) of the 382 cereal crop grower respondents included in the model perfectly predicted.

Accordingly, ten of the fifteen variables included (head's schooling, family size, family labor, livestock ownership, credit use, extension services, use of information, distance to the market, road distance, and nonfarm activities) were found to have a significant association with the level of practicing chemical fertilizer technology. Probit regression results of the current study are similar to the results of (Bayisa, 2014; Beshir, 2014; Beshir, Emana, Kassa and Haji, 2012; Debelo, 2015; Leake, and Adam, 2015; Leake, 2015; Nowak, 1987; Ogada, 2013; Susie, 2017), developed research on practicing chemical fertilizer technology. Specifically, the head's schooling was found to have a strong positive association with adopting decisions. Keeping other factors fixed, each extra year of the head's schooling is expected to result in a 4.8% enhance in the probability of adoption, a statistically significant association ($P < 0.01$). Put differently, households whose head's schooling is higher are more likely to adopt chemical fertilizer technology than the illiterate heads, which is quite significant.

Head's schooling, family size, family labor, and distance to the road were found to have a 1% significant association with adoption decision. Livestock ownership, extension services, distance to the market, and nonfarm activities were found to have a 5% significant association with practicing decisions. Credit use and use of information correlated with adoption decision at 10% significance level. On the other hand, factors such as level of education of the household head, family labor, livestock ownership, credit use,

Table 5. Household characteristics (dummy variables) by adoption status

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

Source: Computed from own survey data 2019/20; Pearson's $\chi 2$ values for categorical/dummy explanatory variables. Figures in parentheses are standard errors.
*** $P < 0.01$

extension service, use of information, and nonfarm activities had all significant positive associations with households' adoption decisions. Family size, distance to the market, and distance to the road had a significant negative correlation with households' adoption decisions Table 6.

Accordingly, eleven of the sixteen variables included (sex, head's schooling, family size, family labor, marital status, participation of cooperative, livestock ownership, credit use, extension services, nonfarm activities, and lambda) were found to have a significant association with the level of intensity of technology adoption decision. Sex, head's schooling, family labor, credit use, extension service, marital status, nonfarm activities, and lambda were found to have a 1% significant correlation with the intensity of adoption decision. Livestock ownership was found to have a 5% significant association with the intensity of technology adoption decisions. Participation of cooperative and family size correlated with the intensity of adoption decision at 10% significance level. On the other hand, factors such as level of education of the household head, family labor, livestock ownership, credit use, extension service, participation of cooperative, and lambda had all significant positive associations with the intensity of households' adoption decisions. Sex, marital status, family size, and nonfarm activities had a significant negative correlation with the intensity of households' adoption decisions Table 7.

Accordingly, the common support region is estimated in Table 8, below the estimated propensity scores matching varies between 0.0456776 and 0.9601382 for participants and 0.03827 and 0.968723 for non-participants. Accordingly, the common support of propensity score matching region was found in the range of 0.0456776 to 0.968723 by discarding 2 cereal crop growers from those participants.

Propensity score matching algorithm can be selected based on balancing test, low Pseudo R-square, large matched sample size, and insignificant LR chi-square. From four used matching algorithms: nearest-neighbor matching (NNM), radius matching (RM), caliper matching CM, and kernel matching (KM), the nearest neighbor matching 4 was the best estimator of the outcomes of the study since it resulted in the least Pseudo R- square 0.027, a large number of matched sample size 380, LR Chi2 = 4.59 and P = 0.884 by deleting 2 adopters from 382of households in Table 9.

Table 10 reports the estimated treatment effects from the propensity score matching. I found that cereal crop chemical fertilizer technology had a significant effect on cereal crop growing

Table 6. Estimates of the determinants of households' decisions adoption (n = 382)

Variables	Robust Coef.	Std. Err.	Odds Ratio	Z-value	P > | z |	dF/dx
Agehh	-1 .0037509	0.03853	0.9985046	-0.40	0.709	-0.0037509
Sexhh	0.645543	0.4672163	1.807583	1.57	0.254	0.2430854
Mshh	-1.2754043	0.6403102	0.5683160	-0.41	0.506	-0.0838025
Fshh	-1.2384221	0.1402197	1.9838723	-2.32	0.002	-0.082799***
Eduhh	0.3353197	0.9281746	1.4263137	2.87	0.007	0.048105***
Alhh	0.2037180	0.1085512	2.7586023	1.98	0.001	0.065703***
Lohh	0.3711719	0.2250681	1.8482102	2.05	0.026	0.094183**
Mchh	0.8781871	0.2700621	2.3721284	2.24	0.530	0.1310015
Aehh	1.0049263	0.9894562	1.9478530	2.03	0.045	0.030763**
Dea	-1.8133917	0.0343842	1.8452794	-1.75	0.482	-0.985672
Achh	0.5803870	0.3073143	1.8836082	1.62	0.076	0.0708203*
Aihh	0.8268131	0.4652873	2.4435621	2.30	0.052	0.020101*
Dmhh	-0.0902171	0.2365746	0.8886070	-1.87	0.037	-0.140070**
Drhh	-2.642065	0.5506206	1.8953821	-2.54	0.003	-0.258044***
Pnfhh	1.7002560	0.5324879	2.1152483	1.71	0.058	0.286279**
Cons.	1.7785235	1.0988421	0. 1411181	1.05	-	-

Source: Computed from own survey data 2019/20; Number of observations = 382; LR chi2 (15) = 84.45; Probability > chi2 = 0.0000; Log likelihood = -97.47; Pseudo R^2 = 0.5028
***, **and * are 1%, 5% and 10% statistically significant levels respectively

farmer food security as evidenced by the significantly larger per capita consumption expenditure and annual income resulting from adoption ($p < 0.01$).

Food consumption expenditure of adopting chemical fertilizer technology of smallholder farmers was much higher than of those who did not 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 more than half the average treatment effect reported implying that the estimated effect associated with the adoption of chemical fertilizer technology is quite large. Similarly, the income of participants of chemical fertilizer technology was also of significantly higher correlation than of those of their non- participant counterparts by 16,573.40 Birr on average in given product year. The average treatment effect also showed that chemical fertilizer technology had a significant impact on Cereal crop production at a 1% significance level ($p < 0.01$) during the 2019/20 cropping season.

The average yields of cereal crops of participant smallholder farmers were higher by 18.50 quintals/ha than non-participant smallholder farmers. This is quite a substantial cereal crop yield enhancement considering the mean cereal crop yield in the Soro District. These outcomes indicate that the adoption of modern chemical fertilizer technology had indeed a significant positive effect on households' food security. In particular, the adoption was associated with significantly higher consumption expenditure, increased annual income, and higher crop yield. Hence, participation of chemical fertilizer technology had a positive effect on the life of the treated showing positive food security impact or alleviation of poverty level on the side of the treated. From consumption expenditure, food consumption expenditure is a better indicator of cereal crop grower wellbeing than crop yield and annual income.

Sensitivity Analysis

Sensitivity analysis is the final diagnostic that must be done to analyze the sensitivity of the estimated treated group effect to small variations in the specification of the model (Grilli and Rampichini, 2011). Sensitivity check is a highly strong evaluating assumption and must be justified. The Q_mh+ and Q_mh- are statistical balance for positive and negative unobserved selection on the impact of chemical fertilizer technology. Both Q_mh+ and Q_mh- give similar findings of the impact of chemical fertilizer technology on cereal crop grower income, consumption expenditure and crop yield. I concluded, based on this concept of sensitivity analysis that the findings were not affected by external effects.

Table 7. Estimates of households' intensification of adoption decisions

Variables	Robust Coef.	Std. Err.	t	P >	z	
Age	0.0654688	0.0758335	1.78	0.709
Sex	- 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

Source: Computed from own survey data 2019/20; Number of observations = 382; Adopter = 287; Non adopter= 95; R^2 = 0.5435; Adj. R^2 = 0.7672;
***, **and * are $P < 0.01$, $P < 0.05$ and $P < 0.10$ statistically significant levels, respectively

Table 8. 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

Source: Own survey 2019/20

Table 9. Selection of matching algorithm

Matching Algorithm		Before matching			After matching		
		Pseudo R^2	LR Chi2	P – value	Pseudo R^2	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

Source: Computed from own survey data 2019/20

Table 10. The average treatment effect

Findings	Adopters	Non - adopters	Difference	BSE	T-stat
Cereal crop yield (Qt/ha)	24.75	6.25	18.50	0.89	3.52***
Annual cereal crop income	25,927.92	9,354.52	16,573.40	12,324.54	3.50***
Food Consumption per capita	24,325.74	10,125.75	14,199.99	12,745.78	5.50***

Source: Computed from own survey data 2019/20, *** $P < 0.01$

This shows that the treatment effect on the treatment is not sensitive to any external variation. In general, the results revealed that there was no hidden bias. Hence, there are no external variables that affect the result determined for average treatment effect on the treated Table 11.

Table 11. Sensitivity check

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

Source: Computed from own survey data 2019/20

Conclusion

This study was focused on investigating the determinants of chemical fertilizer technology adoption, intensity, and impact of technology adoption decisions on household food security among cereal crop growers in Soro district, Ethiopia. The study used primary and secondary data sources. Primary data were collected from interview questionnaires, key informant interviews and focused group discussions. Descriptive and econometric techniques were applied as the methods of data analysis. Particularly, a propensity score matching model was applied to evaluate treated groups with control groups in terms of income, consumption expenditure, and cereal crop yield. Among four matching algorithms the nearest neighborhood matching method 4 was the best estimator of the outcome variables. The findings revealed that the adoption decision of chemical fertilizer technology was associated with significant improvements in household food security as reflected in significantly increased household consumption per capita expenditure and net annual incomes. I also found that adoption was associated with higher yields per hectare among cereal crop-producing farm households. The sensitivity check also revealed that predictions were almost free from unobserved covariates or bias. Consequently, it can be determined that the overall findings are remarkably robust supporting the robustness of the matching techniques.

Moreover, key determinant factors such as the head's schooling, family size, family labor, livestock ownership, credit use, extension services, use of information, distance to the market, road distance, and nonfarm activities were found to be important factors underlying households' adoption decisions. However, there was an insignificant effect of age, sex, marital status, participation of cooperative, and distance to extension agent adoption decisions. The propensity score matching techniques of treated groups were higher by 13.50 quintals of yield per hectare, 16,573.40 ETB annual income, and 14,199.99 ETB food consumption expenditure than those of control groups in the planting season. Therefore, the agriculture and rural development office, extension service office, microfinance office, and other concerned bodies should give important attention to adoption decision, which is a key indicator to alleviate poverty.

Policy Implications

Given these findings, several implications could emerge from my analysis upon which important suggestions could be made as key recommendations. First, even though the adoption of chemical fertilizer technology is relatively low in the Soro District, cereal crop growers who adopted the technology should generally improve their food security and farm productivity. Consequently, the technology could be considered among the components of the agricultural improvement package implemented by local policymakers and actors as part of improving farmers' livelihood in the area. In particular, promoting chemical fertilizer practices in the area could help achieve significant food security and productivity gains thereby leading to better living standards among cereal crop-producing farm households in the area. Secondly, the positive impact associated with adoption necessitates the need for strategies of expanding adoption of the technology among cereal crop producers in the area. In this regard, a better understanding of the factors influencing farmers' choice of planning technique is quite imperative.

More importantly, my findings of the key factors underlying farmers' decisions of adopting chemical fertilizer technology for cereal crop production could serve as an important input for designing policies and strategies aimed at enhancing adoption in the area. For instance, education has a strong association with the adoption of chemical fertilizer technology in cereal crop yields. To this end, strengthening rural farmers' awareness/knowledge among farm households deserves attention for promoting adoption. This is, besides the additional positive adoption-enhancing influence arising from access to extension services – a separate effect from that attributable to better education. Improved provision and access to credits and extension services could also help achieve similar goals. To this end, the use of agricultural extension needs to consider recommended and improved agronomic practices. Extension use is particularly crucial in terms of improving the adoption of chemical fertilizer practices, which can, in turn, enhance cereal crop yields, and subsequent improvements in household food security (food consumption expenditure and household income). Therefore, improving chemical fertilizer technology adoption decision should consequently create income, consumption expenditure and crop yield in a sustainable way.

The research investigated the major differences between the treated and controlled group of cereal crop cultivators through the utilization of chemical fertilizer technology. This research summarized the use of chemical fertilizer technology by policymakers and plan designers and could bring better enhancement to cereal crop cultivators. Improving the application, recommendation, implementation, and practices of such a technology of treated group is a crucial option to enhance cereal crop growers' income, consumption expenditure and crop yield.

References

Admassie A., Ayele G. (2010). Adoption of Improved Technology in Ethiopia. Ethiop J. Econ 19 (1): 155-180. doi: 10.4314/eje.v19i1.71416

Ajayi O. C., Franzel S., Kuntashula E., Kwesiga F. (2003). Adoption of Improved Fallow Technology for Soil Fertility Management in Zambia: Empirical Studies and Emerging Issues. Agrofor Syst. 59 (3): 317-326. doi: 10.1023/B:AGFO.0000005232.87048.03

Akpan S., Nkanta V. S., Essien U. A. (2012). A Double Hurdle Model of Fertilizer Adoption and Optimum Use among Farmers in Southern Nigeria. Tropicultura 30 (4): 249-253

Bayisa G. (2014). A Double-Hurdle Approach to Modeling of Improved Teff Technologies Adoption and Intensity Use: The Case of Diga District of East Wollega Zone, Ethiopia. Global Journal of Environmental Research 8 (3): 41-49. doi: 10.5829/idosi.gjer.2014.8.3.1106

Becerril J., Abdulai A. (2009). The Impact of Improved Maize Varieties on Poverty in Mexico: A Propensity Score-Approach. World Development 38: 1024-1035. doi: 10.1016/j.worlddev.2009.11.017

Beshir H. (2014). Factors Affecting Adoption and Intensity of Use of Improved Forages in North East Highlands of Ethiopia. American Journal of Experimental Agriculture 4 (1): 12-27. doi: 10.9734/AJEA/2014/5481

Beshir H., Emana B., Kassa B., Haji J. (2012). Determinants of Chemical Fertilizer Technology Adoption in Northeastern Highlands of Ethiopia. Journal of Research in Economics and International Finance (JREIF) 1(2): 39-49

Beyene A. (2011). Land Use and Property Right in Northern Ethiopia Smallholder: Farming System. Response to Environmental and Social Change. Lap Lambert Academic Publishing, Germany, pp 224-243

Bezabih E. (2007). Constraints and Opportunities of Horticulture Production and Marketing in Eastern Ethiopia. DCG Report No. 46, 90 pp.

Caliendo M., Kopeinig S. (2008). Some Practical Guidance for the Implementation of Propensity Score Matching. J Econ Surv. 22 (1): 31-72. doi: 10.1111/j.1467-6419.2007.00527.x

Challa M. (2013). Determining Factors and Impacts of Modern Agricultural Technology Adoption in West Wollega, Munich, GRIN Publishing GmbH, Available at: http://www.grin.com/en/e-book/280336/determiningfactors-and-impacts-ofmodern-agricultural-technology-adoption [Accessed 15 12. 2020]

Cochran W. (1977). Sampling Techniques. 3rd ed. New York: John Wiley and Sons, pp 448 - 458

CSA. (2017). Agricultural Sample Survey. Volume I, Report on Area and Production of Major Crops (Private Peasant Holdings, Meher Season), Addis Ababa.

Debelo D. (2015). Analysis of Factors Influencing Adoption of Quncho Teff: The Case of Wayu Tuqa District. J Asian Afr Stud. 12: 20-28

Gebrerufael G., Mahendra P., Tadelle D., Tesfaye S., Alehegn W. (2015). Evaluating the Relative Resistance of Different Poultry Breeds to *Salmonella typhimurium*. Afr J Agric Res. 10 (30): 2928 - 2939. doi: 10.5897/AJAR2014.9425

Greene W. (2007). Econometric Analysis, Sixth Edition. New York, 07458. USA: Pearson Education, Inc., Upper Saddle River.

Grilli., L., Rampichini C. (2011). Propensity Scores for the Estimation of Average Treatment Effects in Observational Studies. Available at: https://www.bristol.ac.uk/media-library/sites/cmm/migrated/documents/prop-scores.pdf [Accessed 10 5. 2020]

Gujarati D. (2003). Basic Econometrics. 4th ed. McGraw-Hill, New York. pp 563-636

Hassen B., Bezabih E., Belay K., Jema J. (2012). Determinant of Chemical Fertilizer Technology Adoption in North-Eastern Highlands of Ethiopia: the Double Hurdle Approach. Journal of Research in Economics and International Finance 1 (2): 39-49

Heckman J. (1979). Sample Selection Bias as a Specification Error. Econometrica 47:153-161. doi: 10.2307/1912352

Heckman J., Ichimura H., Todd P. (1999). Matching as an Econometric Evaluation Estimator. Rev Econ Stud. 65: 261-294

Holden S., Lunduka R. (2012). Do Fertilizer Subsidies Crowd out Organic Manures? The Case of Malawi. Agric Econ. 43 (3): 303-314. doi: 10.1111/j.1574-0862.2012.00584.x

Ibrahim A. A., Mustapha S.B., Nuhu S. H. (2012). Effects of Adoption of Rice Production Technologies on Farmers' Income in Borno State, Nigeria; Department of Agricultural Extension Services, University of, Maiduguri, Nigeria. IOSR J Agric Vet Sci. (IOSR-JAVS) 1 (4): 19-22

IFC. (2013). Working with Smallholders A Handbook for Firms Building Sustainable Supply Chains; World Bank Group. World Bank.

Kapalasa G. (2014). Assessing Factors Influencing Farmers' Adoption of Improved Soybean Varieties in Malawi. Scholarly Journal of Agricultural Science 4 (6): 339-349.

Lavison R. (2013). Factors Influencing the Adoption of Organic Fertilizers in Vegetable Production in Accra, MSc Thesis, Accra Ghana. Available at: http://hdl.handle.net/123456789/5410 [Accessed 05 10. 2020]

Leake G., Adam B. (2015). Factors Determining the Allocation of Land for Improved Wheat Variety by Smallholder Farmers of Northern Ethiopia. J Dev Agric Econ. 7 (3): 105-112. doi: 10.5897/JDAE2014.0621

Leake G. (2015). Factors Influencing Application of Fertilizer by Smallholder Farmers of Northern Ethiopia. J Econ Sustain Dev. 6 (3): 202-207

Lelissa C. (1998). The Determinants of Adoption, Intensity, and Profitability of Fertilizer Use: the case of Ejere District, West Shoa Zone. M.Sc. Thesis. Addis Ababa University, Ethiopia.

Martey E., Wiredu A. N., Etwire P. M., Fosu M., Buah S. S., Bidzakin J., Kusi F. (2014). Fertilizer Adoption and Use Intensity among Smallholder Farmers in Northern Ghana: A Case Study of AGRA Soil Health Project. Sustain Agric Res. 3 (1): 24-36. doi: 10.5539/sar.v3n1p24

Mendola M. (2007). Agricultural Technology Adoption and Poverty Reduction: A Propensity-Score Matching Analysis for Rural Bangladesh. Food Policy 32: 372–393. doi: 10.1016/j.foodpol.2006.07.003

Merge C., Urgessa T. (2014). Determinants and Impact of Modern Agricultural Technology. Adoption in West Wollega: the Case of Gulliso District. Journal of Biology, Agriculture and Health 4 (20): 63-77

Michael M. W., Philip K. T., Keith D. S., Nicholas N. (2007). Factors Affecting the Use of Fertilizers and Manure by Smallholders: A Case of Vihiga, Western Kenya. Nutr Cycling Agroecosyst 78 (3): 211-224. doi: 10.1007/s10705-006-9087-x

MoA. (2012). Ministry of Agriculture. Animal and Plant Health Regulatory Directorate. Crop Variety Register, Issue No.15. Addis Ababa, Ethiopia.

MoFED. (2010). Growth and Transformation Plan (GTP) 2010/11-2014/15 Draft. Addis Ababa.

NBE. (2016). Annual Report of National Bank of Ethiopia. Addis Ababa, Ethiopia. Available at: http://www.nbe.gov.et. [Accessed 10 5. 2020]

Nigussie M., Radicella S., Damtie B., Nava B., Yizengaw E., Ciraolo L. (2012). TEC Ingestion into NeQuick 2 to Model the East African Equatorial Ionosphere, Radio Sci. 47 (RS5002): 1-11. doi:10.1029/2012RS004981

Nowak P. (1987). The Adoption of Conservation Technologies: Economic and Diffusion Explanations. Rural Sociology (USA) 52 (2): 208-220

Ogada M. (2013). Essays on Farm Technology Adoption, Technical Efficiency, and Productivity In Smallholder Food Crop Agriculture In Kenya: Kenyatta University.

Rogers E. (2003). Diffusion of Innovation, 5th ed. New York: The Free Press. J Minim Invasive Gynecol. 14 (6):776. doi: 10.1016/j.jmig.2007.07.001

Rosembaum P., Rubin D. (1983). The Central Role of the Propensity Score in Observational Studies for Causal Effects. Biometrika 70 (1): 41–55. doi: 10.1093/biomet/70.1.41

Samuel G. (2006). Intensification of Smallholder Agriculture in Ethiopia: Option and Scenarios. Future Agriculture. Discussion Paper 007: Available at: http://www.future-agricultures.org [Accessed 12 6. 2020]

Susie T. (2017). Determinants of Adoption of Improved Teff Varieties by Smallholder Farmers: The Case of Kobo District, North Wollo

Zone, Amhara Region, Ethiopia: Msc Thesis Haramaya University, Haramaya.

Thuo M. E., Hathie I., Obeng P. (2005). Adoption of Chemical Fertilizer by Smallholder Farmer in the Peanut Basin of Senegal. University of Connecticut: Senegal.

Uaiene R. N., Arndt C., Masters W. A. (2009). Determinants of Agricultural Technology Adoption in Mozambique. Discussion papers No. 67E January 2009 National Directorate of Studies and Policy Analysis Ministry of Planning and Development Republic of Mozambique.

Winship C., Mare R. D.. (1992). Models for Sample Selection Bias. Annu Rev Sociol 18: 327-350

Wooldridge J. (2013). Introductory Econometrics: A Modern Approach. Mason, OH South-Western Cengage Learning. pp 1-910

World Bank. (2008). Agriculture Development Report Agriculture for Development.The World Bank. Washington, DC, USA. doi: 10.1596/978-0-8213-6807-7 [Accessed 10 5. 2020]

World Bank. (2014). Ethiopia Poverty Assessment. Document of the WB for Official Use only.

Yuko N., Kei K. (2012). The Determinant of Technology Adoption: A Case of Rice Sector in Tanzania. International Rice Research Institution: Dar es Salaam. Available at: https://www.researchgate.net/publication/254 [Accessed 14 5. 2020]

aCS87_19