JOURNAL OF SMART ECONOMIC GROWTH

JSEG

www.jseg.ro ISSN: 2537-141X Volume 7, Number 1, Year 2022

IMPACT OF CHEMICAL FERTILIZER ON YIELDS AMONG SMALLHOLDER FARMERS: THE CASE OF SIBU SIRE WOREDA, ETHIOPIA

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Abstract: *This study analyzed the impact of technology adoption decisions on the yields of smallholder households in the study area. The data used for the study were obtained from 191 randomly selected sample households in the study area. The average treatment effect of adoption on household yield was estimated by using the propensity score matching method. The propensity score matching estimation showed that the average yields of adopters are greater than that of non-adopters. Since income and income proxy variables have a significant influence on the likelihood of farmers' adoption income diversification interventions could have a pay-off. The PSM result showed that the positive effects of chemical fertilizer adoption on farm household yields. Since adopters are in a better position; appropriate strategies that increase the intensity of use for the adopter and encourage non-adopter to use chemical fertilizer on their farmland should be promoted and that there is a large scope for enhancing the role of chemical fertilizer in contributing to promoting production.*

Keywords: Propensity Score Matching, Impact, Chemical Fertilizers, sensitivity test

1. Introduction

As available arable land is becoming increasingly scarce improvements in production will be derived largely by the intensification of inputs rather than expansion of land areas which calls for chemical fertilizer consumption as a key element of any agricultural strategic plan. Since the need of the rapidly growing population could not be met by expanding the area under cultivation, developing, employing, and disseminating yield-increasing agricultural technologies is imperative. Thus, the intensification path and the practice of letting the land lie fallow for long periods are rapidly becoming impractical [1]. The economic behavior of farmers in developing countries is guided by the traditional practices which are barriers to the process of development and these countries remain poor and often have been designated as 'traditional'. Traditionalism is one of the major constraints in technology adoption. The rural farmers depend on indigenous or local knowledge for improved farming system/ animal husbandry. Agricultural tools and practices employed by the smallholder farmers of Ethiopia had been in use for more than a century. Now a day beside the traditional practices of farmers there are options available to them that can help to improve their products such as improved seeds, high yield varieties, and chemical fertilizer and pest side [2].

Increasing productivity through expansion of chemical agricultural technology is a key, if not the only, 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 [3], especially as a way to tackle land degradation, low agricultural productivity, and poverty. The slow development of the agriculture sector could be a constraint for the rest of the economy if it is not efficient enough to supply food and raw materials to the industrial sector.

It is imperative to deliver appropriate technology to the farmers and motivate them to adopt it. It is therefore essential for national planners and extension educators to know what technology the growers are using and what sources of information are used and what the main determinants of adopting or not adopting are. Researchers should undertake impact evaluation on different programs launched by the government to promote production and productivity whether the program attains the intended ultimate goals. Many different chemical fertilizer adoption studies were undertaken in SSA countries and Ethiopia [4;5;6;7;8;9;10&11]. However, most of those studies were limited in dealing with identifying the factors affecting the adoption decision of the framers. Thus, the present study was expected to provide recent empirical evidence on factors determining chemical fertilizer adoption among smallholder farmers.

2. Model specification

2.1 Model for Impact analysis

Propensity score applied when program participation is none randomly assigned. It evaluates the treatment effect in the case of two groups of 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 [12]. 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 adopters. Thus, the control group is generated which will be observationally the same as 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 a large group of non-treated who are observationally similar to participants in terms of characteristics not affected by the program (these can include preprogramming characteristics, for example, because those are not affected by subsequent program participation). Different approaches are used to match participants and nonparticipants based on the propensity score. They include nearest-neighbor (NN) matching, caliper and radius matching, stratification and interval matching, and kernel matching, and local linear matching (LLM) [13].

The procedure of calculating ATT based on propensity score match method is similar with the [14], 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 the adoption of chemical fertilizer by farm households in Sibu sire woreda will be analyzed through the 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 farmland.

The 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 adopts 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:

$$Y = DY1 + (1)Y0 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (1)$$

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

$$ATT = E(Y_1 - Y_0|D = 1) = E(Y_1|D = 1) - E(Y_0|D = 1) \ldots\ldots\ldots\ldots\ldots\ldots (2)$$

The 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 in random conditional on observed covariates X [15] (that means 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:

$$E(Y_0|X, D = 1 = E(Y_0|X, D = 0) = (Y_0|X). \ldots\ldots\ldots\ldots\ldots\ldots\ldots (3)$$

This assumption rules out adoption based on 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:

$$ATT = E(Y_1 - Y_0|X, D = 1) = E(Y_1|X, D = 1) - E(Y_0|X, D = 1) \ldots\ldots\ldots\ldots (4)$$

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.

2.2 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. To compensate for the lack of randomization, treated and control units are often matched based on 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 the 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 into treatment and the outcome variable simultaneously a hidden bias might arise to which matching estimators are not robust [16]. In participation probability given by:

$$Pi = P(xi, ui) = P(Di = 1|xi, ui) = F(\beta xi + \gamma ui) \ldots\ldots\ldots\ldots (5)$$

Where xi is the observed characteristics for individual i, ui is the unobserved variables and γ is the effect of ui 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 groups with the same observed covariates x have different chances of receiving treatment. The selectivity test evaluates how the program effect is affected by a change in γ. The following bounds on the odds ratio of the participation probability of both individuals are applied.

$$\frac{1}{e^r} \leq \frac{pi(1-pj)}{pj(1-pi)} \leq e^r \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (6)$$

The study conducted by [16] both individuals have the same probability of participation if e^r=1. e^r is a measure of the degree of departure from a study that is free of hidden bias. 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 econometric analysis was employed sequentially in this chapter.

3. Results and Discussion

3.1 Descriptive Analysis

Under this paper, descriptive analysis was taken using the mean, mean difference between the two groups and making discussion on their significant covariates. Table 1 in the appendix shows the mean value of each group and the mean difference of all covariates with their respective t-values. The average age of all sample respondents is about 45 years which indicates the highly productive range of the labor force. On the other hand, the mean age of chemical fertilizer adopters is 40 while that of non-adopters is 49. Non-adopters are 9 years older than the adopters. This result shows the fact that as farmers become older, they become risk averters and resist new technologies. The mean age difference of adopters and non-adopters is 9 which is significant at 1%.

Education is one of the factors which affect positively the decision to adopt the technology. Educated farmers adopt new technology more quickly than their counterpart illiterates and thus education is an instrument through which technology will be defused to agriculture and promote productivity thus tackling hunger and poverty. From the survey data, the mean education level of adopters is grade 7 and that of non-adopters is grade 3 with a significant mean difference of grade 4. This shows that adopters are more educated than non-adopters. The average number of classes attended by all the sample households is about 5.

Adopter has less experience than non-adopter with 25 and 38 years respectively. The mean experience difference between adopter and non-adopter is about 13 is also significant. Income is the key factor that enhances the purchasing power and mostly farmers with a higher level of income can purchase modern technology and become an adopter. The mean income of all sample households is 11842.9 and for adopter and non-adopter of chemical fertilizer is 14982.54 and 6122.52 birr respectively with a mean income difference of 5936.67 birr which is significant. Adopters get on average 5937 more birr annual than non-adopters.

The family dependency ratio is negatively affected by family number; families with large family sizes have a high dependency ratio which impends major socio-economic decisions made. The average family number of the total sample is about 5. Adopters have on average 5 family members and non-adopters have 6. The mean difference of family members is significant at 5 %.

Livestock is a proxy variable to wealth. Wealthier families adopt new technology more likely than the poor. Livestock is measured using Tropical Livestock Unit (TLU). The mean tlu of adopters is about 20.57 while that of non-adopter is 16.28. This shows that adopters have more livestock than non-adopters with a mean difference of 4.28 and significant.

Contact with DA is one major factor that affects the decision of farmers to adopt new technology. In a country where major of the population is illiterate and/or where vast of them attain a lower level of education extension service is a key instrument by which knowledge and new technology are transmitted. The mean day of adopters getting extension service per year on their farmland is about 2 days while those non-adopters on average get the service about one day per annual. The mean difference is 1.36 and is significant.

Due to cultural barriers females are not expected to make a major decisions in their families. Since chemical fertilizer adoption is a major decision in the rural economy sex plays a decisive role. From the total sample of households, 73.83% of them are male while the remaining 26.17% are female. Out of the total female adopters and non-adopter are 20% and 80% respectively. The male counterpart indicates 56.74% of them are an adopter and the remaining 43.26% are non-adopters. The result from Table 2 in the appendix shows that there is a statistically significant difference between the mean value of the male and female-headed adopter and non-adopter households at a 1% probability level.

In a rural economy, there are different means of livelihood; the farmer can get income from different sources. Off-farm income is the main source of income to support the major agricultural activities. Participation in off-farm activities increases the source of income for the farmer and affect positively their decision to adopt new technology thus off-farm income enhances their capability to purchase new technologies. From the total sample, about 53.4% of them participate in off-farm activities while the remaining 46.6% did not participate. Finding from the survey data shows that there is a statistically significant difference between the mean value of off-farm participant and non-participant between adopter and non-adopter.

3.2 Econometric modeling

3.2.1 Propensity score

Under this study, the Propensity score matching model uses a logit model to estimate the probability of each group (adopter and non-adopter) as a function of observable covariates. The result of the propensity score of program participants and their counterparts is used to define the common support region. Further, the quality of matching algorithms was also identified about the propensity scores pseudo-R^2 and significance level of each covariate. Table 3 in the appendix shows that the logit estimation results of sample households in the program were used to create propensity scores. Eleven variables sexh, ageh, eduhh, farmexp, extension, tlu, offfarm, hhsize, tlandarea, income, and ecology were used. The result shows that nine variables were significantly influenced the program participation.

Ageh, tlu, offfarm, hhsize, tlandarea and income are significantly affecting the likelihood of program participation at a 5% level of probability while sexh, eduhh and extension are significant at 10% level. Among the variables, age of household and household family size affect the likelihood of participation in the program negatively as expected whereas the remaining variables have a positive effect. The Pseudo R^2 which enlightens how well the repressors explain the participation probability is 0.485 as shown in Table 3 in the appendix.

Depending on the propensity score distribution of both adopter and non-adopter the common support region is identified. As shown in Table 4 in the appendix shows that the estimated propensity scores vary between 0.0892 and 0.9994 for the program participant and 0.000633 to 0.9089 for non-participant. The common support region is an area that lies between0.0892 to 0.9089. Households whose estimated propensity score is less than 0.0892 and larger than 0.9089 are discarded from the common support region thus 42 households from program participants were out of the common support region.

3.2.2 Matching algorithms

Three matching algorithms such as the nearest neighbor, radius caliper, and the kernel were checked to choose the best matching methods. The choice of matching estimators was based on pseudo R^2, matching sample size, and mean test referred to as to balance test. Low pseudo R^2 value, large matched sample size, and insignificant mean difference between the two groups are preferable. Thus, depending on the criteria discussed above nearest neighbor (5) was selected in which the mean difference of the two groups explanatory variables were insignificant, pseudo R^2 is the lowest compared to other matching categories, and finally balance 149 sample size.

3.2.3 Testing the balance of propensity score and covariates

The common support or overlap condition assumes that units (farmers) with the same covariate values have a positive probability of being both treated and untreated.PS distributions appear with sufficient common support region that allows for matching. PSM requires the fulfillment of the balancing property, i.e., the covariate means between members and nonmembers should be similar after matching. The objective of this property is to verify that treatment is independent of unit characteristics after conditioning on the observed covariates. As shown in Table 6 in appendix matching reduce total bias, reduce pseudoR^2 from 0.48 before the match to 0.062 after the match and any difference between the two groups covariates mean in the matched sample has been reduced and after matching all variables become insignificant and were balanced.

The ATT is estimated depending on the nearest neighbor. As the result from Table 7 in the appendix indicates the difference in mean yield of adopter of chemical fertilizer and the matched non-adopter are 17.52 quintals. The mean difference between both groups is highly significant with a t-value of 8.83. Adopter harvest 17.52 quintals more than the matched non-adopter and this figure has a monetary value of Birr 6132 in current price; thus, the program has a positive effect on increasing yields of program participants which can foster their income, improve their living conditions and in general reduce their poverty situations.

3.2.4 Sensitivity Test

To check for unobservable biases, using the Rosenbaum Bounding approach sensitivity analysis was performed on the computed outcome variables. In this study, sensitivity analysis was carried out on the estimated average treatment effect using alternative matching estimators for yield. The results show that the effect of adoption does not change, even though the participant and non-participant households were allowed to differ in their odds of being treated up to 300% (e^{γ}=3) in terms of unobserved covariates. Thus, impact estimates (ATT) is insensitive to unobserved selection bias, in the rage of e^{γ} is 1.8 and 2 and the result is pure effects of adoption.

4. Conclusion and Policy Implication

The study gives more focus on factors determining adoption and intensity of use of chemical fertilizer by using the Heckman selection model and analyzing the impact of chemical fertilizer use on yield through PSM. Under econometrics probit result shows that farmers' probability of adopting chemical fertilizer is affected significantly at 10% by sex of household heads, contact to DA, the number of household family, and income. On the other hand, age of household head,

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education level, livestock number in tlu, off-farm participation, and total land area have significantly affected the livelihood of adoption at 5%. The result of OLS reveals that livestock number, the total land area was significantly affecting the intensity of use at 10% while income at 5%. The PSM result shows that a positive effect of chemical fertilizer/agricultural technology adoption on farm household yields. Since adopters are in a better position; appropriate strategies that increase the intensity of use for the adopter and encourage non-adopter to use chemical fertilizer on their farmland should be promoted and that there is a large scope for enhancing the role of chemical fertilizer in contributing to promoting production.

It is important to consider both adoption and intensity used in scheming and evaluating strategies aimed at promoting the adoption and use of chemical fertilizer. Both stages should get due attention in transforming the agricultural sector. Skill developing training that could diversify the income source of the farmers should be provided for the farmers and attention should be given to the area where the farmers can generate additional income especially on off-farm activities.

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Appendix

Table 1: showing means, standard deviations, and mean difference of continuous variables for both adopters and non-adopters calculated

Variables	Total Sample	Adopter	Non-adopter		
	Mean (Std. Dev.)	Mean (Std. Dev.)	Mean (Std. Dev.)	Mean diff.	t-value(P>t)
Ageh	44.53 (9.06)	39.84 (7.98)	48.72 (7.87)	8.87	7.72 (0.000) ***
Eduhh	4.7 (3.8)	6.6 (3.73)	2.99 (2.99)	-3.6l	-7.413 (0.000) ***
Farmexp	31.81 (11.84)	25.30 (10.13)	37.62 (10.13)	12.32	8.3814(0.000) ***
Income	11842.9 (7342.27)	14982.54 (7352.4)	9045.5 (6122.52)	-5936.67	-6.085 (0.000) ***
Hhsize	5.48 (1.38)	4.87 (1.29)	6.02 (1.22)	1.16	6.375 (0.022) **
Tlu	18.3 (5.85)	20.57 (5.79)	16.28 (5.14)	-4.28	-5.43 (0.000) ***
Contact to DA	1.51 (1.32)	2.23 (1.33)	0.87 (1.05)	-1.36	-7.87 (0.000) ***
Tlandarea	1.711 (0.621)	1.85 (0.7)	1.59 (0.51)	-0.265	-0.3747 (0.030) **

Source: Computed from own survey data 2016; ***, ** and * implies significant at 1%, 5% and 10% probability level, respectively

Table 2: Table showing mean, of discrete variables for both adopters and non-adopters calculated

Variables	Adopter (%)	Non adopter (%)	Pearson chi square value

Sex of the household heads	Female	20	80	
	Male	56.74	43.26	19.99***
Off-farm participation	participate	62.74	37.26	
	Not participate	29.21	70.79	21.45***

Source: Computed from own survey data 2016; ***, ** and * implies significant at 1%, 5%, and 10% probability level, respectively; Notes: the percentage was computed from the total sample (191).

Table 3: Logit estimate of propensity score

Variable	Coef.	SE	P >|Z|	dy/dx
Sexh	0.859	0.481	0.074*	0.215
Ageh	-0.144	0.073	0.049**	-0.340
Eduhh	0.145	0.077	0.059*	0.035
Farmexp	0.047	0.053	0.378	0.0122
Extension	0.389	0.21	0.065*	0.022
Tlu	0.09	0.043	0.027**	0.022
Offfarm	0.955	0.469	0.042**	0.224
Hhsize	-0.375	0.203	0.065*	-0.087
Tlandarea	0.861	0.426	0.43	-0.208
Income	0.000082	0.000036	0.023**	0.075
Ecology	0.354	0.29	0.222	0.000018
Cons.	0.41	2.066	0.984	

Source: Computed from own survey data 2016; Sample size 191; Log likelihood = -68.023573; LR chi2 (11) = 128; Prob > chi2 = 0.0000; Pseudo R2 = 0.4850; **and * show level of significance at 5% and 10% respectively.

Table 4: Distribution of estimated propensity score

Observations	Mean	Std. Dev.	Min.	Max.
Non adopters	0.215	0.222	0.0006334	0.9089

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www.jseg.ro ISSN: 2537-141X Volume 7, Number 1, Year 2022

Adopters	0.7608	0.2834	0.0892	0.9994
Total	0.4723	0.3738	0.00063	0.9998

Source: Computed from own survey data 2016

Table 5: Performance of matching estimators

Matching estimator		Balancing test	pseudo R2	Matched sample size
NN	1	42	0.08	149
	2	42	0.082	149
	3	42	0.073	149
	4	42	0.067	149
	5	42	0.062	149
KM	0.01	64	0.087	127
	0.1	42	0.080	149
	0.25	42	0.080	149
	0.5	42	0.080	149
RM	0.01	64	0.114	127
	0.1	42	0.76	149
	0.25	42	0.085	149
	0.5	42	0.092	149

Source: Computed from own survey data 2016

Table 6: Propensity score and covariates balancing

Variable	Unmatched Matched	Mean		Reduction bias %	p>|t|
		Treated	control		
Sexh	Unmatched	0.777	0.866		0.21
	Matched	0.687	0.74	-11.8	0.562
Ageh	Unmatched	39.67	44.933		0.000***
	Matched	42.688	43.775	-14.0	0.529
Eduhh	Unmatched	6.7	2.28		0.000***

	Matched	5.08	5.25	-5.2	0.861
Farmexp	Unmatched	25.22	29.11		0.003***
	Matched	29.33	29.92	-5.8	0.809
Tlu	Unmatched	20.3	21.09		0.306
	Matched	18.83	18.48	6.3	0.774
Extension	Unmatched	2.11	1.87		0.002***
	Matched	1.604	5.31	-22.8	0.271
Hhsize	Unmatched	4.866	5.31		0.006***
	Matched	5.31	5.25	4.3	0.832
Tlandarea	Unmatched	1.82	1.7		0.147
	Matched	1.69	1.54	24.7	0.266
Offfarm	Unmatched	0.711	0.811		0.001***
	Matched	0.604	0.525	16.8	0.2995
Ecology	Unmatched	0.933	0.811		0.191
	Matched	0.812	0.575	30.2	0.122
Income	Unmatched	15,343	19,559		0.001***
	Matched	12,435	14,112	-24.4	0.2995

Source: own computation based on survey data 2016; *** show level of significance at 1%

Table 7: Estimating the impact of agricultural technology adoption decision

Outcome variable	Treated	Controls	ATT	S. E	T-stat
Yield (Qt/ha)	60.27	42.75	17.52	1.95	8.83***

Source: Computed from own survey data 2016