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Analysis of the Impact of Organic Fertilizer Use on Smallholder Farmers' Income in Shashemene District, Ethiopia

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Abstract: Ethiopia's agricultural sector accounts to 40 percent of the national Gross Domestic Product. The sector is important in improving the livelihoods of the bulk of the population. Despite its importance, the agricultural sector in Ethiopia is characterized by low productivity. To improve this, the Ethiopian government has focused on promotion of adoption of organic fertilizer. However, empirical evidence on the impact of organic fertilizer on farmers' income is lacking in most parts of Ethiopia, specifically in Shashemene district. This study therefore aimed at evaluating the impact of organic fertilizer adoption on households' farm income. Primary data was collected from 155 adopters and 213 non-adopters of organic fertilizer. Adopters were selected systematically while non-adopters were selected randomly. The study used propensity score matching to analyse the data. The results showed that the adoption of organic fertilizer increased farmers per hectare farm income by 2661 ETB to 2959 ETB. Thus, farmers should be encouraged to adopt organic fertilizer through improving provision of better extension services, which incorporates relevant trainings to the farmers and better access to information related to organic fertilizer as well as making availability of this for farmers easier through encouraging its commercialization.

Keywords: Organic Fertilizer, Agriculture, Propensity Score Matching

1. Introduction

In Ethiopia, about 86 percent of total export earnings is obtained from agriculture (MoFED (Ministry of Finance and Economic Development), 2010). The sector makes a significant contribution to the national GDP and provides a basis for development of other sectors such as industry. About 40 percent of the country's GDP is generated from agriculture. It is also the main source of income for 85 percent of people living in rural areas of the country consisting of more than 90 percent of the Ethiopian poor (IFPRI (International Food Policy Research Institute), 2010). Therefore, the sector is important in improving the livelihoods of the bulk of the population.

As such, reducing poverty levels as well as improving food security necessitates creation of a better performing agricultural sector in the country. This is thus the goal of the government and several development partners. In its first phase of five year growth and transformation plan (2010/11-2014/15), the Ethiopian government had placed emphasis on agriculture and rural development to reduce rural poverty and improve overall economic growth (IFDC (International Fertilizer Development Centre), 2012). Based on the achievements, agriculture continues to be targeted in the second growth and transformation plan (2015/16 – 2019/20) giving priority to smallholder agriculture (Ethiopian National Planning Commission, 2015). The plan focuses on ensuring farmers reap maximum benefits from the agricultural sector (MoFED, 2015). To achieve this, the government has promoted different agricultural technologies in addition to scaling up the best practices of better performing farmers in overall sustainable improvement of agricultural productivity.

The major focus of the intervention was adoption of new agricultural technologies by smallholder farmers. Such technologies include use of organic fertilizer as the main yield-augmenting technology. This is because unlike mineral fertilizer, organic fertilizer can stay in the soil as a further soil amendment for a long period leading the soil to be fertile on sustainable basis so that improving farmers' income from the sector. However, there is a dearth of information about the impact of adoption of this specific technology on farmers' professional income. Thus, this study intended to evaluate the impact of organic fertilizer on households' income in the Shashemene district, Ethiopia.

2. Literature Review

Many scholars have proposed agricultural intensification as a way of increasing agricultural productivity. This can be possible through adoption of agricultural technology (Uaiene *et al*. 2009). Due to this, in most parts of Ethiopia, the adoption of technologies such as organic fertilizer continues to be necessary to increase agricultural productivity. To ensure this sustainably, it is important to clearly address the impact of this fertilizer on households' farm income.

According to Kassa *et al.* (2014), the adoption of organic fertilizer has positive impact on the agricultural productivity. They revealed that fertilizer adopters get better yield hence more income compared to their non-adopter counterparts. The Institute for Sustainable Development (2007) showed that productivity can be increased by more than double if organic fertilizer is used compared to when mineral fertilizer is used, while IFPRI (2010) revealed that productivity increases by 10-20 percent when comparing these fertilizer practices, thus increasing household income. This shows that the adoption of organic fertilizer is important for improving productivity thus contributing to increased farmers income. This has been possible through increasing yield with marginal increase in total cost of organic fertilizer use (Cooke 1972, cited in Lavison, 2013). Further, the difference in the impact of organic fertilizer use on farm productivity across literatures (IFPRI, 2010; Institute for Sustainable Development, 2007) show that there is a tendency of the effect being location specific calling for evaluation of the impact this type of technologies in different farming sites.

3. Methodology

3.1. Study Area, Sampling Procedure and Sources of Data

This study was carried out in Shashemene district of Ethiopia. The district is situated 7°05' to 7°19' North and 38°23' to 38°41' East. It is found in West Arsi zone of Oromia regional state and located 250 km south of Addis Ababa, the capital of Ethiopia. The district is bordered on the South by SNNPR state, on the North by Arsi Nagelle district, on the East by Kore district, on the South east by Kofele district and on the West by Shalla district. Its climate is characterized as temperate with annual temperature ranging from 12°C to 27°C. It is 1,685 m to 2,722 m above sea level and has a population of about 42,942. More than 85% depend on agriculture for their livelihood where majority of them are smallholders owning a plot of less than 5 hectares.

The study targeted smallholder farmers where two stage sampling technique was used to identify respondents. In the first stage, purposive sampling of *kebeles* was done leading to the selection of Wotera turufe elemo, Ilala korke, Kerara filicha, and Butte filicha *kebeles*. These *kebeles* have relatively more organic fertilizer adopters. In the second stage, systematic sampling was used to choose a sample of adopters of organic fertilizer whereas simple random sampling technique was used to sample non-adopters. Following Yamane (1967) the required sample size of 368 respondents was determined of which 58% were non-adopters and 42% were adopters of organic fertilizer.

3.2. Data Analysis Technique

Farmers choose either to adopt or not to adopt a given technology based on expectations, objectives, and observable and unobservable characteristics. This is referred to as self-selection (Chala and Tilahun, 2014). Thus, simple comparison of the adopters with non-adopters tends to overestimate the impact of improved agricultural technology on farmers income. To overcome this problem, propensity score matching (PSM) has been used as the best procedure. In impact analysis, if the dimensions of the covariates are many, individual matching on the basis of observed covariates may not be feasible. Thus, instead of matching along covariates, matching along the propensity scores may provide better results. Hence, recently, several studies have used this procedure to evaluate the impact of agricultural technologies on the households' income (Acheampong and Owusu, 2014; Chala and Tilahun, 2014; Awotide *et al.,* 2012; Nguezet *et al*., 2011).

Propensity score matching (PSM) has an advantage of reducing dimensionality of matching to a single dimension (Chala and Tilahun, 2014). It is the best possible procedure to evaluate the individual probability of receiving the treatment given the observed covariates (Rosenbaum and Rubin, 1983). It determines the average treatment effect on the treated farmers (organic fertilizer adopters). That is, the causal effect of adoption of organic fertilizer on the farmers per hectare farm income (average income from wheat, maize, *teff*, and beans). This is done in the final stage while PSM estimates propensity scores and checks for balancing conditions in the first step. The scores can be estimated for treatment variables using probit model (Mendola, 2007). This study was thus employed the probit model to predict the propensity scores using socio-economic and institutional variables. The effectiveness of PSM depends on two assumptions. These are assumption of conditional independence and assumption of common support.

Conditional independence assumption (CIA): This assumption states that the selection into the adoption group is solely based on the observable characteristics. Given the values of some observable covariates, this assumption implies that the value of the outcome variable is independent of the treatment state. This means the household's income should be independent of adoption assignment. Therefore, the organic fertilizer adopters' outcome and the non-adopters' outcome is independent of the treatment status.

$$Y_0,\ Y_1 \perp A \mid Z \tag{1}$$

$$E\,(Y_1 \mid P, A_i = 1) = E\,(Y_0 \mid P, A_i = 0) \tag{2}$$

Where, P is i^{th} farmer propensity of organic fertilizer adoption, Y_1 is outcome (income) of i^{th} farmer when organic fertilizer is adopted, Y_0 is outcome of i^{th} farmer when organic fertilizer is not adopted, E is expectation operator, and A is the state where i^{th} farmer adopts or not adopt organic fertilizer; 1 for a farmer who has adopted organic fertilizer and 0 otherwise.

Equation (2) shows that the adopters could have the same average farm income as non-adopters if they would have not participated in adoption of organic fertilizer controlling all pre-program observable household characteristics that are correlated with the program participation and the outcome variable (Adelman *et al*., 2008). Thus, the non-adopters outcome can be used as an unbiased estimator of the counterfactual outcome for the adopters.

Common support assumption (CSA): This assumption states that the average treatment effect for the treated (ATT) is only defined within the region of common support. It also assumes that no explanatory variable predicts the treatment perfectly.

$$0 < \mathrm{p}\,(A = 1 \mid Z) < 1 \tag{3}$$

If the above two assumptions are satisfied, then conditional to estimates of propensity scores (p), the observed outcome (average income) of organic fertilizer adopters can be substituted for the missing average income of the non-adopters.

Given that the propensity scores are balanced and the above assumptions are satisfied, according to Rosenbaum and Rubin (1983) the parameter of interest which is average treatment effect on treated (ATT) can be estimated as:

$$\begin{aligned} ATT &= E(y_1 - y_0 / A = 1) \\ &= E(y_1 / A = 1) - E(y_0 / A = 1) \end{aligned} \tag{4}$$

Where, y_1 is outcome (income) of i^{th} farmer when organic fertilizer is adopted, y_0 is outcome of i^{th} farmer when organic fertilizer is not adopted, E is expectation operator, and A is the state where i^{th} farmer adopts or not adopt organic fertilizer; 1 for a farmer who has adopted organic fertilizer and 0 otherwise.

In impact evaluation, the interest is not on $E\left(y_0 / A = 0\right)$, but on $E\left(y_0 / A = 1\right)$. Therefore, PSM uses estimated propensity scores to match the observed mean income of the non-adopters who are most similar in observed characteristics with adopters. This means, it uses $E\left(y_0 / A = 0\right)$ to estimate the counterfactual $E\left(y_0 / A = 1\right)$. Then:

$$\begin{aligned} ATT &= E(y_1 - y_0 / A = 1) \\ &= E\left[E\left(y_1 - y_0 / A = 1, p(z)\right)\right] \\ &= E\left[E\left(y_1 / A = 1, p(z) - E(y_0 / A = 1, p(z) / A = 1\right)\right] \\ &= E\left[E\left(y_1 / A = 1, p(z) - E(y_0 / A = 0, p(z) / A = 0\right)\right] \end{aligned} \tag{5}$$

Where; *ATT, E,* y_1, y_0, p and A are defined as earlier and the outer expectations are defined over the distribution of $\mathrm{p}(A = 1/X)$.

A number of proposed methods are available to deal with matching similar adopters and non-adopters. Nearest neighbour matching method (NNM), radius matching method (RM), stratification matching method (SM) and kernel based matching method (KM) are the most commonly used methods based on similarity of propensity scores among the observations.

The choice of a specific matching algorithm depends on the data in question, and in particular on the degree of overlap between the treatment and comparison groups in terms of the propensity score (Berhe, 2014). It is also stated that consideration of several matching algorithm in tandem is advantageous as it allows measuring the robustness of the impact estimates (Becker and Ichino, 2002).

3.3. Sensitivity Analysis

One of the central assumptions of the sensitivity analysis is that treatment assignment is not unconfounded given the set of covariates (z). This implies that the Common Support Assumption (CSA) no longer holds. It is also assumed that the assumption of conditional independence (CIA) holds given z and an unobserved binary variable (U). Where;

$$\mathrm{U}\!: Y_0 \perp\!\!\!\perp D \mid (\mathrm{z}, U)$$

As long as U is existing and unobserved, the outcome of the controls; $\mathrm{E}\,(Y_0 \mid D = 0)$ cannot be credibly used to estimate the counterfactual outcome of the treated; $\mathrm{E}\,(Y_1 \mid D = 1)$. This means:

$$E(Y_0 \mid D = 1, \mathrm{z}) \neq E(Y_0 \mid D = 0, \mathrm{z}) \tag{6}$$

Conversely, if U is known together with the observable covariates (z), then it would have been possible to estimate ATT using the outcome of controls. This is because:

$$E\,(Y_0 \mid D = 1, \mathrm{z}, \mathrm{U}) = \mathrm{E}\,(Y_0 \mid D = 0, \mathrm{z}, \mathrm{U}). \tag{7}$$

Considering the following equation with binary potential outcomes,

$$Y = D * Y_1 + (1 - D) * Y_0$$

The distribution of the binary confounding factor U is fully characterized by the choice of four parameters:

$$p_{ij} = p(u=1|D=i, Y=j) = p(u=1|D=i, Y=j, z) \quad (8)$$

In order to make the simulation of the potential confounder feasible, two simplifying assumptions are made. These are the assumption of binary U and conditional independence of U with respect to z. It was also indicated that the simulation assumptions pointed out here have no impact on the results of the sensitivity analysis (Ichino, Mealli and Nannicini, 2006). Using a given set of values of the sensitivity parameters, the matching estimation is repeated many times and a simulated estimate of the ATT is retrieved as an average of the ATTs over the distribution of U. Then, the simulated U is treated as any other observed covariate and included in the set of matching variables to estimate the propensity score and compute ATT according to the chosen matching algorithms.

4. Results and Discussion

4.1. Descriptive Statistics

Table 1 presents the averages and *t*-values of continuous variables while Table 2 presents the proportions and *chi*^{2} results of the selected categorical socio-economic variables. The data set contains 368 observations, of which 42% were adopters and 58% were non-adopters of organic fertilizer. The results indicated that the mean farm size, group membership, extension visits and highest education level within family was significantly different between the adopters and non-adopters of organic fertilizer. Besides, the mean of the household heads' education, highest education level within family, household size, labour, farm size, experience, group membership, credit and extension visit was higher among the adopters of organic fertilizer compared to the non-adopters. Further, the results show that some variables did not exhibit significant mean difference between the groups of adopters and non-adopters of organic fertilizer. However, there is a variation in the averages of these variables among the groups (Table 1).

Table 1. *Results on Age, Education, Household size, Labour, Farm size, Income, Farming Experience, Group membership, Credit, Extension visits and Distance.*

	Adopters		Non adopters		Overall mean	Test statistics
Characteristics	Mean	SD	Mean	SD		*t*- value
Age (years)	43.99	11.00	44.20	11.88	44.11	-0.17
Household head education (years)	6.35	3.84	5.74	3.39	5.99	1.61
Highest education in the family (years)	10.65	2.90	10.10	3.01	10.33	1.75*
Household size (family number)	7.26	3.01	7.02	3.36	7.13	0.71
Labour (number)	3.27	2.76	2.95	2.70	3.09	1.11
Farm size (hectares)	1.06	0.53	0.86	0.40	0.94	4.06***
Experience (years)	23.97	10.57	23.89	11.16	23.93	0.07
Group membership (number)	0.59	0.52	0.31	0.49	0.42	5.31***
Access to credit (amount in ETB)	4100.00	1780.45	3582.98	1978.86	3737.31	-1.55
Extension (number of extension visit)	3.67	2.79	2.86	2.61	3.20	2.85***
Distance to the nearest market (km)	3.57	2.42	3.61	2.30	3.59	-0.71

Note, *** and * indicate significance at 1% and 10% respectively while SD denotes standard deviation.

The results of categorical variables showed that majority (88.4% of the adopters and 88.7% of the non-adopters) of the households were male headed both among the organic fertilizer adopters and non-adopters. In relation to marital status, 96.1% of the household heads were married among the adopters while the remaining 3.9% were widowed. On the other hand, 94.4%, 3.3%, 1.9% and 0.5% were married, widowed, single and divorced respectively among the non-adopters. Regarding farm fertility, 72.9%, 23.9% and 3.2% of the organic fertilizer adopter households perceived that their farms were medium, not fertile and fertile respectively. About 74.6%, 22.1% and 3.3% percent of the non-adopters believed that their farms were medium, not fertile and fertile respectively. About 83.2% of the households had access to information media among the adopters whereas 13.8% did not. Among the non-adopters, 69.9% of the households had access to information media while 30.1% did not. Further, access to information media was significantly correlated with adoption decision of organic fertilizer while farm fertility, gender and marital status was not (Table 2).

Table 2. *Results on Gender, Marital status, Farm fertility and Access to information media (radio and television).*

		Adopters		Non-adopters		Test statistics
Characteristics		Freq.	%	Freq.	%	x^2- value
Gender	Male	137	88.4	189	88.7	0.01
	Female	18	11.6	24	11.3	
Marital status	Single	0	0.0	4	1.9	3.75
	Married	149	96.1	201	94.4	
	Divorced	0	0.0	1	0.5	
	Widowed	6	3.9	7	3.3	

Characteristics		Adopters Freq.	%	Non-adopters Freq.	%	Test statistics x^2- value
Farm fertility	Not fertile	37	23.9	47	22.1	
	Medium	113	72.9	159	74.6	0.17
	Fertile	5	3.2	7	3.3	
Access to information media	Yes	129	83.2	149	69.9	8.56***
	No	26	16.8	64	30.1	

Note, *** denotes significance at 1%.

4.2. Econometric Results

4.2.1. Estimation of Propensity Scores

The household's agricultural income per hectare of farm land for the year 2014/15 was used for impact assessment. Taking participation (adoption decision) as 1 if the household has been participating in adoption of organic fertilizer and 0 otherwise, propensity scores were estimated using probit regression. All variables hypothesized to influence adoption decision of organic fertilizer were included to predict the probability of each household's participation in organic fertilizer adoption. These variables include: age, gender, household size, education level of household head, income, experience, farm size, perception of farm fertility, access to credit, extension visits, access to information through information media, membership to farmer groups, labour, marital status, distance to the nearest market and highest education level among the family members'. The Chi^2 results given by 56.74 and the corresponding test statistic ($p < 0.000$) suggests that the included explanatory variables of the model were capable of explaining the farmers' propensity of participating in adoption of organic fertilizer. Farm size, extension visits, access to information media (radio and television), membership to farmer groups, distance to the nearest market and marital status of the household head significantly affected probability of households' participation in adoption of organic fertilizer.

Table 3. *Probit results of farmers' participation in adoption of organic fertilizer.*

Covariates	Coef.	Std. Err.	*Z*
Age	0.004	0.011	0.36
Gender	0.100	0.254	0.40
Household size	-0.024	0.032	-0.76
Household head education	0.040	0.025	1.60
Experience	-0.003	0.010	-0.30
Farm size	0.534***	0.183	2.92
Farm fertility	-0.118	0.150	-0.79
Credit amount	0.000	0.000	-1.49
Extension visits	0.054**	0.026	2.10
Access to information media	0.432**	0.179	2.42
Membership to farmer groups	0.427***	0.145	2.94
Distance to the nearest market	0.219*	0.123	1.78
Marital status	0.340*	0.198	1.71
Number of labour	0.012	0.046	0.26
Family's highest education	0.022	0.027	0.81
Constant	-2.589	0.862	-3.00
N	368		
LR ch^2 (15)	56.740		
Prob. > chi^2	0.000		
Pseudo R^2	0.113		

Note, ***, ** and * indicate significance at 1%, 5% and 10% respectively.

The overall estimated propensity scores lie between 0.033 and 0.902 (Table 4). Amongst the adopters of organic fertilizer, the propensity scores vary between 0.109 and 0.902 while amongst the non-adopters it lie between 0.033 and 0.790. This shows that the region of common support would lie between 0.109 and 0.790 dropping outliers below and above this range. Out of 368 households, 9 of them (9 from the adopters and 0 from the non-adopters of organic fertilizer) were dropped from the analysis because of their propensity scores falling outside the region of common support. Thus, it seems that the included observations (359 households) are sufficient to predict the impact of organic fertilizer on households' farm income for this study. Furthermore, the propensity scores results showed that the overall average propensity score among the sampled households was about 0.42 implying that the average probability of participating in adoption of organic fertilizer for individual sampled households was about 42 percent.

Table 4. *Distribution of the estimated propensity scores.*

Categories	Obs	Min	Mean	Max	SD
Organic fertilizer non-adopters	213	0.033	0.360	0.790	0.166
Organic fertilizer adopters	155	0.109	0.507	0.902	0.187
Total	368	0.033	0.422	0.902	0.189

4.2.2. Choice of Matching Algorithms

The choice of matching algorithms was guided by the criteria's such as number of balanced covariates after matching (number of covariates with no statistically significant mean difference between adopters and non-adopters of organic fertilizer after matching), Pseudo-R^2 and matched sample size. A matching estimator that balances all covariates and bears low psuedo-R^2 value as well as with large matched sample size is preferable for impact assessment (Tolemariam, 2010). After looking into the results presented in Table 5, based on the above discussed criterion, kernel matching and nearest neighbour matching (NN (6)) were equally found to be the best matching methods in assessing the impact of organic fertilizer adoption on households' farm income. Therefore, both matching algorithms were used in the impact assessment of this study. Since the results of the performance analysis for kernel matching showed equal number of balanced covariates, equal Psuedo-R^2 and equal matched sample size for all included band width (0.06, 0.1, 0.25, and 0.5), any one of the listed band width can be used to perform the analysis. This study has therefore chose the band width of 0.06.

Table 5. *Results on performance of different matching algorithms.*

	Performance evaluation criterion		
Matching estimators	**Balancing test***	**Psuedo-R^2**	**Matched sample size**
Nearest neighbour matching			
NN (1)	15	0.020	359
NN (2)	15	0.016	359
NN (3)	15	0.007	359
NN (4)	15	0.008	359
NN (5)	15	0.007	359
NN (6)	15	0.004	359
Radius matching			
Calliper of 0.01	15	0.005	363
Calliper of 0.25	14	0.020	359
Calliper of 0.50	11	0.080	359
Kernel matching			
Band width 0.06	15	0.004	359
Band width 0.10	15	0.004	359
Band width 0.25	15	0.004	359
Band width 0.50	15	0.004	359

Note, * Number of covariates exhibited no significant mean difference after matching between adopters and non-adopters of organic fertilizer.

4.2.3. Testing the Balancing Properties of Propensity Scores and Covariates

Before estimating the impact of organic fertilizer adoption on households' farm income, the balancing properties of propensity scores should be checked to test whether the observations have had the same distribution of propensity scores or not. According to Tolemariam (2010), balancing test seeks to examine if at each value of the propensity score, a given characteristic has the same distribution for the treated and comparison groups. The results presented in Table 6 show that five variables exhibited significant mean difference before matching while no variable showed significant mean difference after matching. This implies that there is high degree of covariate balance between the sample participants and non-participants of organic fertilizer adoption. Therefore, it was concluded that the specification used in this study was successful in terms of balancing the distribution of covariates between the matched adopters and non-adopters of organic fertilizer.

Table 6. *Balancing test of the covariates based on kernel matching method.*

	Pre-matching (N = 368)			Post-matching (N = 359)		
Covariates	**Treated**	**Control**	***t*-test**	**Treated**	**Control**	***t*-test**
Age	43.99	44.20	-0.17	44.00	43.48	0.40
Gender	0.88	0.89	-0.10	0.88	0.87	0.09
Household size	7.26	7.02	0.71	7.18	7.08	0.27
Household head education	6.35	5.74	1.61	6.26	6.27	-0.02
Experience	23.97	23.89	0.07	23.95	23.78	0.13
Farm size	1.06	0.86	4.06***	1.02	0.99	0.57
Soil fertility	1.79	1.81	-0.37	1.81	1.80	0.17
Credit amount	529.03	828.17	-1.55	561.64	527.84	0.19
Extension visits	3.67	2.86	2.85 ***	3.59	3.64	-0.14
Access to information media	0.83	0.70	2.95 ***	0.82	0.82	0.00
Membership	0.59	0.31	5.31***	0.55	0.57	-0.20
Distance to nearest market	1.08	0.98	1.53	1.06	1.02	0.44
Marital status	2.08	2.05	0.63	2.07	2.09	-0.51
Labor	3.27	2.95	1.11	3.23	3.12	0.32
Family's highest education	10.65	10.10	1.75*	10.57	10.57	-0.01

Note, *** and * indicate significance at 1% and 5% respectively.

In addition to the above results, the overall (joint) test statistics for the balancing properties showed that Pseudo-R^2 was 0.004 for the matched observations which was fairly low. The p-value for the corresponding Pseudo-R^2 and likelihood ratio test was insignificant at conventional probability level ($p > chi^2 = 0.999$) confirming that both the treated (adopters of organic fertilizer) and control (non-adopters of organic fertilizer) groups had the same distribution of covariates after matching. This further showed that the employed model was the most robust and complete therefore allowing comparison of households' per hectare average farm income between the adopters and non-adopters of organic fertilizer who share common support in terms of propensity scores. The results of the chi-square test for the joint significance of variables are presented in Table 7.

Table 7. *Results of chi-square test for joint significance of variables.*

Sample	**Pseudo R^2**	**LR chi^2**	***p* – value**
Pre-matching	0.113	56.74	0.000***
Post-matching	0.004	1.50	0.999

Note, *** indicates significance at 1% probability level.
Source: Author survey data, 2016

4.2.4. Impact of Organic Fertilizer Adoption on Households' Farm Income

The results presented earlier (section 4.1) showed that the kernel based matching algorithm and nearest neighbour matching with six closest neighbour could give the best results of the impact assessment for this study. However, according to Becker and Ichino (2002), consideration of several matching algorithms in tandem is advantageous as it allows measuring the robustness of the impact estimates. Thus, in addition to kernel matching and nearest neighbour matching, radius matching and stratification matching methods were also employed to compare the difference of average farm income between the samples of adopters and non-adopters of organic fertilizer. Accordingly, the results indicated that the households who adopted organic fertilizer had earned 2661 ETB to 2959 ETB more average per hectare farm income compared to non-adopters of organic fertilizer (Table 8). This implies that, adoption of organic fertilizer is crucial to increase farmers' farm income. The nearest neighbour matching, stratification matching and kernel based matching results were significant at 5 percent probability level while the results for the radius matching were significant at 1 percent probability level. Kassie *et al.* (2009) posited that the use of compost had led to significant increase in yield of wheat, barley and *teff* grains in Tigrai region of Ethiopia while Lavison (2013) noted that there was better net income when vegetable producing farmers used organic fertilizer instead of mineral fertilizer in Accra, Ghana. According to Institute for Sustainable Development (2007) and IFPRI (2010), farm productivity can be increased by more than 10 percent when organic fertilizer is used compared to when mineral fertilizer is used. Moreover, the results suggest that adoption of organic fertilizer contributes to increased farm income among the farmers in Shashemene district of Ethiopia.

Table 8. *Propensity score matching results.*

Matching Algorithms	Number of treated	Number of controlled	ATT	Std. Err.	*t*-value
NNM	146	213	2733.54	1045.75	2.61**
KM	146	213	2665.22	1011.87	2.63**
SM	147	217	2660.66	1016.20	2.62**
RM	154	209	2958.62	913.42	3.24***

Note, *** and ** show significance at 1%, and 5% respectively.

Where, NNM is nearest neighbour matching (NN (6)), KM is kernel matching (band width = 0.06), SM is stratification matching and RM is radius matching (calliper = 0.01).

4.2.5. Results of Sensitivity Analysis

The main purpose of this analysis is to check or estimate the degree at which the estimated treatment effects were free of unobserved covariates. This could be done through comparing baseline treatment effects and simulated treatment effects or through comparing the values of outcome effects and selection effects generated by *sensatt* with the predetermined values of outcome and selection effects. The results presented in Table 9 show that the simulated outcome effect was 1.2 for the nearest neighbour matching and kernel matching while it was 1.22 for radius matching. The selection effects were 19.23, 18.85, and 19.19 for nearest neighbour matching, radius matching and kernel matching methods respectively. According to Nannicini (2007), outcome effect measures the observed effect of unobserved covariates on untreated outcome while selection effects measure the effect of unobserved covariates on the selection into the treatment. This means, in this study, for the estimated impact of organic fertilizer adoption on households' farm income to be invalid, there would have been unobserved confounder that can increase the relative probability of organic fertilizer adoption by a factor of 18.85 to 19.23 and also increase positive treatment outcomes by a factor of 1.2 to 1.22 which is not plausible. On the other hand, comparing the simulated and base line ATT, the initial estimates were free of unobserved covariates by about 95 percent for the nearest neighbour and radius matching while the estimates were free of unobserved covariates by about 94 percent for the kernel based matching algorithm. This shows that the matching results were almost insensitive to the potential unobservable bias and therefore the estimated ATT were pure effects of organic fertilizer adoption.

Table 9. *Simulation based sensitivity analysis results.*

Matching Algorithms	Simulated ATT	Std. Err.	Outcome effects	Selection effects
NNM	2592.35	1875.20	1.20	19.23
RM	2799.64	1096.02	1.22	18.85
KM	2512.14	.	1.20	19.19

Where, NNM is nearest neighbour matching, RM is radius matching and KM is kernel matching.

5. Conclusions

This study aimed at evaluating the impact of organic fertilizer adoption on households' farm income in Shashemene district, Ethiopia. Primary data was collected from 155 adopters and 213 non-adopters of organic fertilizer in the district. Propensity score matching method was employed for data analysis. The results indicated that there was significant difference in average per hectare farm income between the adopters of organic fertilizer and non-adopters. Using different matching algorithms, the households who adopted organic fertilizer had earned better average per hectare farm income compared to the non-adopters counteract. They earned more farm income (average income from wheat, maize and beans) by 2661 ETB to 2959 ETB from a unit hectare of cultivation plot. This implies that the adoption of organic fertilizer had positive impact on households' farm income in the study area. Despite this advantage, adoption of organic fertilizer remains low in Shashemene district due to some factors such as inadequate information regarding organic fertilizer use and less availability of sources of organic fertilizer. However, to enhance adoption of organic fertilizer amongst smallholder farmers, government and other stakeholders should target provision of better extension services, which incorporates relevant trainings to the farmers and better access to information related to organic fertilizer as well as making availability of organic fertilizer for farmers easier through encouraging commercialization of this fertilizer.

Further, it was observed that majority of the farmers were uncertain about how frequent the application of organic fertilizer should be. Thus, to fill this gap, further studies within agronomy are required.

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