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The Impact of Village Poultry Technology Adoption on the Livelihood of Smallholder Farmers in Central Oromia Region, Ethiopia

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Abstract
The study was conducted to assess the impact of village poultry technology adoption on smallholder farmers in central Oromia Region, Ethiopia.Using multi-stage random sampling method, 180 technology participants were selected for face to face interview. Structured questionnaire was employed to collect data. Propensity score matching (PSM) Logit model was used to test the impact of the technology. The study revealed that adopters were significantly benefited by 68.5% from the technology and could produce 101 more eggs per/layer, consumed 18 more eggs/year and got 168.65 Birr more income per layer/year as compared to non-adopters. In conclusion, improved chicken breeds intervention had positive impact on average treatment effect on treated (ATT) and average treatment effect (ATE) on study population. Except livelihood change, the significant differences between adopters and non-adopters on outcome variables were not due to hidden bias but due to the treatment effect of technology intervention.
Keywords: Adoption, Impact, Propensity score matching, Village poultry technology

1. Introduction

Measuring impact is important in providing essential tools to evaluate systematically the relative efficacy of various types of interventions but there are no 'gold standards' for measuring many interventions impact (Catley *et al.* 2008). However, a well designed impact assessment can capture the real impact of interventions, be they are positive or negative, intended or unintended on the livelihood of the participants. Successful adoption of improved agricultural technologies could stimulate overall economic growth through inter-sectoral linkages (Sanchez *et al.* 2009) and it has a significant positive impact on farmers' integration to output market (Asfaw *et al.* 2010). For instant, in rural areas of Bangladesh, agricultural technologies adoption has robust and positive impact on poverty reduction and on well-being of the households' (Mendola 2007).

In Africa, adoptions of improved agricultural technologies had positive impacts on income, food security and poverty reduction (Asfaw *et al.* 2010; Wanyama *et al.* 2010*)*. In Ethiopian condition, adoptions of improved agricultural technologies have positively and significantly affected household's food security (Ferede *et al*. 2003). For instance, adoption of improved chickpea varieties has a positive and vigorous effect on market and reduces food insecurity of adopter households (Asfaw *et al.* 2010). Similarly, in Southeastern part of Ethiopia, adoption of improved wheat technologies has a robust and positive effect on farmers' food consumption per adult equivalent per day (Mulugeta & Hundie 2012). To improve village poultry production, Ethiopian Ministry of Agriculture and Rural Development developed and disseminated village poultry technology (improved chicken breeds). Many households were participated on the technology; however, the impact of the technology intervention was not efficiently assessed in different agro-ecological zones of the country as other agricultural technologies. Therefore, this study was conducted to assess the impact of the village poultry technology adoption on participant smallholder farmers in central Oromia Region, Ethiopia.

2. Materials and Methods

2.1 Description of the study areas

The study was conducted in the central part of Oromia Region located between 3°24'20" to 10°23'26"N latitudes and 34°07'37" to 42°58'51"E longitudes (OBoFED 2008). The region is characterized by vast geographical and climatic diversity having three major climatic categories called dry, tropical rainy and temperate rainy climates. Three districts, namely *Wolmera, Ade'a* and *Boset* were selected based on agro-ecology and history of village poultry technology package distribution.

2.2 Sampling procedures and data collection

Three districts *Wolmera* (highland), *Ade'a* (mid-altitude) and *Boset* (lowland) were purposely selected based on their agro-ecology and village poultry technology intervention (CSA 2012). From each district, 5 *Kebeles* (farmers' administrations) were randomly selected; and using multi-stage random sampling method, 180 technology participants (73 adopters and 107 non-adopters) were selected from participant lists (12 participants per *Kebele*). Structured questionnaire was used for face to face interview. The questionnaire was pre-tested and adjusted prior to the actual survey. The data collection focused on benefit from the technology, impact of the technology on knowledge and skill improvement, livelihood change, egg production change (difference of eggs produced per layer/year after and before participation), egg consumption change (difference of eggs used for family consumption per year after and before participation) and income change (difference of income per layer/year after and before participation).

Variables definition

Table 1. Variables types and their definition

Variable type	Abbreviation	Variable definition
Treatment variable	CHICKADO	Adopted improved chicken breeds (0=No, 1=Yes)
Covariates	SEX	Sex of the respondent (0=Male, 1=Female)
	AGE	Age of the respondent (years)
	FAMSIZE	Family size of the respondent (number)
	LANDHOLD	Landholding of the respondent (hectare)
	CHCKFEXP	Chicken farming experience of the respondent (years)
	TECHEXPI	Technology experience (0=Up to 5years, 1= > 5 years)
	FRETECH	Frequency of technology received (0=Once, 1= > twice)
	EXTSERVI	Did you get extension services? (0=No, 1=Yes)
	HLTHSERV	Did you get healthcare services? (No=0, 1=Yes)
	TRAINING	Did you get training the technology? (0= No, 1=Yes)
	MARKETDS	How far the town market from your farm? (km)
Outcome variables	KNOWSKIL	Technology improved knowledge and skill?(0= No, 1=Yes)
	BENEFIT	Did you benefit from the technology? (0= No, 1=Yes)
	LIVEHOOD	Technology brings positive changes on livelihood? (0= No, 1=Yes)
	EGGPRO	Change of egg production per layer/year (number)
	EGGCONS	Change of egg consumption for family per year (number)
	INCOME	Income change per hen per year (Birr)

2.3 Theoretical framework

This study hypothesized that village poultry technology (improved chicken breeds) adoption has a positive impact on the livelihood of technology participants. According to AIEI (2013), impact evaluation designs can be non-experimental to compare the outcomes of the technology between the treated and control groups. Since this study observational study, non-experimental impact evaluation design was used to analyze the data using propensity scores matching (PSM) method (Rosenbaum & Rubin 1983). According to Caliendo & Kopeinig (2005), propensity score is the probability of the participants for observed characteristic X. Propensity score matching method compares average outcomes of the adopters and non-adopters based on estimated propensity score values. If technology was randomly assigned to farmers, the causal effect of technology adoption can be assessed by comparing the difference of variables between treated and untreated, however, the technology is rarely randomly assigned in non-experimental studies which results self-selection bias (Wu *et al.* 2010). When treatments were not randomly assigned, it was difficult to determine casual inferences whether the difference in outcome between the treated and control groups was due to the treatment effect or other characteristics. The PSM method can estimate average treatment effect of the technology adoption (Caliendo & Kopeinig 2005).

2.4 Statistical analysis

To assess impact of technology adoption, 11 covariates were used. Prior to the analysis, variance inflation factor (VIF) test for continuous variables and contingency coefficient (CC) test for discrete variables were conducted to check whether there is multi-collinearty problem existed among the covariates according to (Gujarati 2004; Berhanu 2012). Similarly, whether there is problem of hetroscedasticity among the covariates, Breusch-Pagan/Cook-Weisberg “hottest” test was carried out according to (Wooldridge 2002). Generalized linear model (GLM) mean procedure and frequency analyses were used to analyze the socio-economic characteristics of the respondents using SAS version 9.0 software packages. Propensity score “pscore” command of STATA version 12.0 software packages was used to estimate the p-scores. Propensity score matching “psmatch2” command was used to assess the impact of technology adoption on the livelihood of smallholder farmers. For sensitivity analysis “rbounds” bounding approach was used to check wither there is hidden bias due to unobservable variables.

2.4.1 Econometric model

Estimation of propensity scores

According to Caliendo & Kopeinig (2005), in the implementation of PSM five steps are required. These are pscores estimation, choosing matching algorithm, checking for common support, matching quality/effect estimation and sensitivity analysis. Logit model was used to estimate propensity scores (pscores). To solve self-selection problem, PSM method was used as the conditional probability of receiving a treatment (adoption) of observed characteristics (Rosenbaum & Rubin 1983). Then the treated (adopted) groups were matched with non-treated (non-adopted) groups on the basis of pscores and the average effect of the technology was calculated as the mean difference in outcome of the two groups. The analytical framework 'treatment effect' for individual was defined as the difference between farmer adopted the technology $T_i = 1$ and not, $T_i = 0$ as follows:

$$\mathcal{T}_i = Y_i(1) - Y_i(0) \ldots\ldots\ldots (1)$$

Where $\mathcal{T}_i$ was treatment effect, Y_i was the outcome on a participant i, whether a participant T_i had adopted village poultry technology or not.

Since both Y_i (T=1) and Y_i (T=0) couldn't be observed at the same time on the same participant, there was counterfactual outcome. Due to this, estimating individual treatment effect $\mathcal{T}_i$ was not possible. For this shifting to estimating the average treatment effects of the population was required. Based on this, the average treatment effect on the treated ($\mathcal{T}_{ATT}$) was defined as:

$$\mathcal{T}_{ATT} = E(\mathcal{T}|T = 1) = E[Y(1)|T = 1] - E[Y(0)|T = 1] \ldots\ldots\ldots (2)$$

And average treatment effect (ATE) of the overall population was defined as the difference between average treatment effect of adopters and non-adopters as follows:

$$\mathcal{T}_{ATT} = E[Y(1) - Y(0)] \ldots\ldots\ldots (3)$$

However, in observational study since the treatment was not assigned randomly, there was self-selection bias. To solve this self-selection bias, ATT could be denoted as:

$$E[Y(1)|T = 1] - E[Y(0)|T = 0] = \mathcal{T}_{ATT} + E[Y(0)|T = 1] - E[Y(0)|T = 0] \ldots\ldots\ldots (4)$$

And the true parameter $\mathcal{T}_{ATT}$ was only identified if and only if there was no self-selection bias. According to Caliendo & Kopeinig (2005), to solve self-selection bias, conditional independence assumption (CIA) and common support assumptions were used. Where in CIA a set of observable covariates *X* were not affected by the treatment assignment and the potential outcomes were independent of treatment assignment defined as:

$$Y(0), Y(1) \coprod T|X, \forall X \ldots\ldots\ldots\ldots\ldots\ldots. (5)$$

Where $\coprod$ denoted independence

This implies selection was only based on observable characteristics and all variables that influenced treatment assignment and potential outcomes were simultaneously observed. According to Rosenbaum & Rubin (1983) balancing scores, if potential outcomes are independent of treatment conditional covariates X, they are also independent of treatment conditional on balancing score *b(X).* Therefore, based on the probability of propensity score, CIA could be defined as:

$$Y(0), Y(1) \coprod T|P(X), \forall X \ldots\ldots\ldots\ldots (6)$$

Where P and ∀ denoted probability and for both groups, respectively

In common support assumption was checking overlaps and identification of common support region for both adopters and non-adopters. The common support condition requires the existence of sufficient overlap in the characteristics of the adopter and non-adopter units to find adequate matches (Mulugeta & Hundie 2012). Since common support condition was one of the further required for perfect predictability of treatment for a given covariate X, it was defined as:

$$0 < P(T) = 1|X < 1 \ldots\ldots\ldots\ldots (7)$$

By considering CIA and common support assumptions, the PSM estimator for ATT was the mean difference in outcomes over the common support (p-score distribution) expressed as:

$$\mathcal{T}_{ATT}^{PSM} = E_p(X)|T = 1\{E[Y(1)|T = 1, P(X)] - E[Y(0)|T = 0, P(X)]\} \ldots\ldots\ldots (8)$$

Where P(X) was the propensity score computed on the covariate Xs.

Choosing of matching algorithm

To choose the best matching algorism calliper radius, nearest neighbour and kernel matching estimators were conducted to match the adopters with non-adopters. All matching estimators compare the outcome of treated individual with outcomes of untreated (Caliendo & Kopeinig 2005). Therefore, after estimating the probability values on the observable covariates, matching was done using selected a matching algorithm based on the available data at hand. Even though different matching algorisms were used, the final decision to choose the appropriate matching estimator was based on balancing test, relatively low pseudo-R^2 value and largest matched sample size (Dehejia & Wahba, 2002).

Checking overlap/common support region

According to Caliendo & Kopeinig (2005), in PSM average treatment effect on treated (ATT) and average treatment effect (ATE) on population are only defined in the common support region. The common support region is the region within the minimum and maximum propensity scores of treated (adopters) and control (non-adopters) groups, respectively. Based on this, the common support region for the current study was done by discarding those observations whose pscores were smaller than the minimum and greater than the maximum of both the adopters and non-adopters (comparison groups).

Assessing match quality/effect estimation

After choosing the best fitted matching estimator, the next procedure in PSM analysis was testing the covariate balance to check the balancing property of the covariates by comparing the significant test difference before and after matching using the selected matching algorism. To check the balance distribution of relevant variables in both the control and treated groups, the before and after covariates matching should be checked (Caliendo & Kopeinig 2005). This study assessed the matching quality to check the balance distribution the variables. Balance test was conducted to know whether there was significant difference in mean value of per-treatment characteristics of both adopter and non-adopter respondents. According to Rosenbaum & Rubin (1985) standardized bias (SB) is used to assess the marginal distance of covariates and *t*-test is used to check whether there is a significant difference in covariate means for both groups in the common support region (check matching quality). According to Tolemariam (2010), a matching estimator having insignificant mean differences in all covariates, having low pseudo-R^2 value and resulting large matched sample size was preferred as a best matching quality. Since testing the statistical significant of treatment effects and computing their standard errors is not straightforward (Caliendo & Kopeinig 2005), bootstrapping method (popular method) was used to solve this problem and to compute the standard error for the estimate of the technology impact (Lechner 2002; Mulugeta & Hundie 2012). Since the matching quality test this study suggests that the chosen matching algorithm was relatively best for the data, estimating the average treatment effect on the treated (ATT) was the next task.

Sensitivity analysis

Since ATT matched outcome variables estimations show significant, ssensitivity analysis was the final (fifth) step conducted in order to check the robustness of the estimation (whether there were hidden biases affected the estimated ATT or not). Respondents KNOWSKIL improvement ATT t-test shows insignificant, therefore it was not considered in the sensitivity analysis. According to Keele (2010), when outcome indicators showed significant, two things should be done in sensitivity analysis in order to check whether there are hidden biases or not. These are sensitivity analysis on the p-values and see how the p-value increases for increasing values of degree of departure from random assignment of treatment (Γ) and how the magnitude of the treatment effect changes with an increasing Γ where each sensitivity test is built on a specific randomization test for a type of outcome. Since the lower bounds Hodges-Lehmman point estimates under underestimated the true treatment effect, upper binds were used according to Becker & Caliendo (2007). Based on CIA, the treatment effect could be estimated with matching estimators on selected observable characteristics. However, unobserved variables which affect assignment to the treatment and the outcome variable simultaneously might result hidden bias called unobserved heterogeneity (Caliendo & Kopeinig 2005). Since it was not possible to estimate the magnitude of selection bias with non-experimental data, this problem was address using "rbounds" bounding approach proposed by Rosenbaum (2002).

3. Results

3.1 Socio-economic characteristics of the respondents

In this study, 65.6% and 34.4% of the respondents were male and female, respectively. The age of the respondents ranges from 19-74 years with mean of 42 years. The family size ranges from 1-12 with a mean of 6 per household. About 38.9% of the respondents had nil or less than 1 hectare farmland and most (65.6%) of them had less than 2 hectare of farmland. The chicken farming experience ranges 5-58 years with mean of 20.8 years. Most of the respondents (47.8%) had 16-30 years of chicken keeping experiences. About 46.1% and 53.9% of the respondents have up to 5 and over 5 years of village poultry technology package experiences, respectively.

3.2 Impact of technology adoption

Variance Inflation Factor (VIF) test for continuous covariates and contingency coefficient test for categorical variables were less than 10 and 0.75, respectively. Similarly, Breusch-Pagan/Cook-Weisberg test for heteroskedasticity among covariates had p=0.9754 which is insignificant. Theses imply that there were no multicollinearity and heteroskedasticity problems existed among the covariates thus no variable was dropped from the model.

3.2.1 Propensity score estimation

The estimated pscores of the covariates are indicated in Table 1. The pseudo-R^2 value of the estimated model resulted 0.1108 which was fairly low. The pscores estimation show, respondents who were older, had more chicken keeping experience and far from market were less likely to participate on technology. Participation on improved chicken breed technology was positively and significantly influenced by extension (P<0.01) and training (P<0.05) services. The logit estimated intercept was (-0.567) negative and insignificant.

Table 1. Estimated of the propensity score for explanatory variables

Variable	Coefficient	SE	Z-value	P-value
SEX	0.292	0.359	0.81	0.416
AGE	-0.027	0.025	-1.10	0.272
FAMSIZE	0.023	0.079	0.29	0.772
LANDHOLD	0.059	0.129	0.45	0.650
CHCKFEXP	-0.00005	0.023	-0.00	0.998
TECHEXPI	0.180	0.362	0.50	0.620
FRETECH	0.559	0.399	1.40	0.161
EXTSERVI	1.063	0.352	3.02**	0.003
HLTHSERV	0.061	0.384	0.16	0.873
TRAINING	0.730	0.350	2.09*	0.037
MARKETDS	-0.029	0.024	-1.22	0.223
Constant	-0.567	0.930	-0.61	0.542

Number of observation = 180; LR χ^2 (11) = 27.02; Prob > χ^2 = 0.0046; Pseudo-R^2 = 0.1108; Log likelihood = -108.39801

** =p≤0.01, *=p≤0.05

3.2.2 Choosing of matching algorithm

As indicated in Table 2, nearest neighbor 5 (NN 5) matching estimator fulfilled the balancing test (equal means) that indicates all covariates were included in the model and insignificant mean differences between the two groups after matching, had relatively low pseudo-R^2 value and resulted largest sample size (matched sample size). Thus, NN (5) was identified the best model fitted matching estimator for this study. In pscore estimation and performing initial balance of the covariate, 4 numbers of blocks were identified that ensured the mean pscore was not different for adopters and non-adopters in each blocks.

Table 2. Matching performance of different estimators

Matching estimator	Performance criteria		
	Balance test*	Pseoud-R^2	Matched sample size
Radius caliper			
0.1	11	0.068	123
0.25	11	0.080	128
0.5	11	0.078	142
Nearest neighbor			
NN (1)	11	0.040	169
NN(2)	11	0.020	169
NN(3)	11	0.018	169
NN(4)	11	0.012	169
NN(5)	11	0.008	169
Kernel			
Band width 0.1	11	0.011	169
Band width 0.25	10	0.049	169
Band width 0.5	9	0.072	169

**Number of explanatory variables with insignificant mean difference between the matched groups of adopter and non-adopter.*

3.2.3 Common support region

The estimated pscores ranges from 0.123 to 0.782 with a mean 0.495±0.17 for adopters and ranges from 0.105-0.735 for non-adopters with a mean 0.352±0.17. By discarding observations whose estimated pscores fall outside, the common support region was identified. Therefore, common support region ranges 0.123 to 0.735 which means households whose estimated pscores less than 0.123 and larger than 0.735 were not considered for the matching purposes. As a result, 11 households (3 adopters and 8 non- adopters) were discarded from the analysis. Figure 1 and 2 show the distribution of households with respect to the estimated pscores of the adopters and non-adopters, respectably in the common support condition. As shown in Figures, most of the adopter households were distributed in the right side while most of non-adopters households were distributes in the left side. There was wider area in which both the groups had in common where most of the adopters had pcore around 0.6 while majority of the non-adopters had around 0.2.

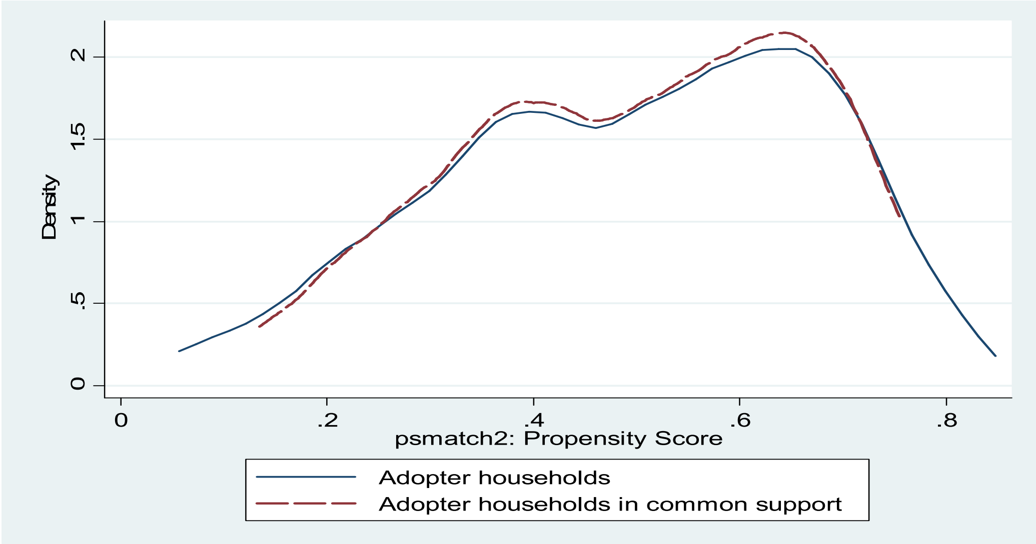

Figure 1. Kernel density of adopter households in the common support region

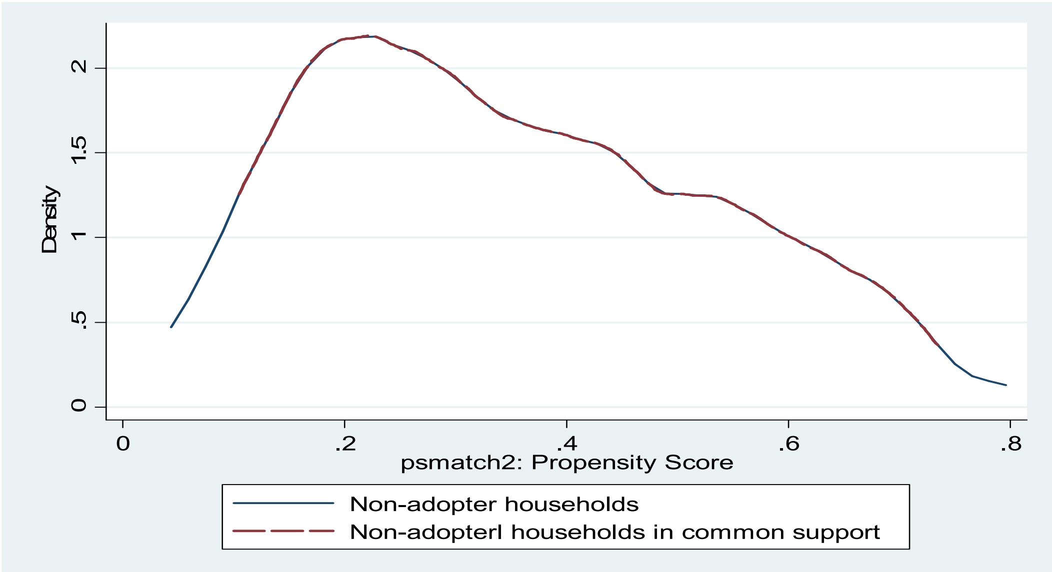

Figure 2. Kernel density of non-adopter households in the common support region

3.2.4 Matching quality/effect estimation

Before matching, 27.8% of the covariates pscore estimates show significant but after matching all show insignificant. The balancing efficiency of the estimator was determined by considering the reduction of the mean SB between the matched and unmatched respondents and equality of means (adopters and non-adopters) was tested using t-test. As shown in Table 3, fifth column shows the mean BS before and after matching while sixth column shows the total mean SB reduction obtained by the matching procedure. The absolute value of unmatched means difference ranges from 4.4-82.6% and 3 of the covariates (27.8%) were significant. However, after they matched, the absolute value of SB reduction ranges from 0.1-9.6% and the t-test show insignificant with low Pseudo-R^2 (0.008) that means all covariates were included (balanced) in the model.

Table 3. Testing of covariates balance for adopters and non-adopters

Variable	Unmatched Matched	Mean Treated	Mean Control	%bias	%reduction /bias/	T-test T	T-test P>/t/
pscore	Unmatched	0.495	0.352	82.6		5.45***	0.000
	Matched	0.484	0.482	1.1	98.6	0.07	0.945
SEX	Unmatched	0.378	0.321	12.0		0.80	0.426
	Matched	0.366	0.392	-5.3	56.0	-0.31	0.758
AGE	Unmatched	41.205	42.896	-16.4		-1.08	0.281
	Matched	41.538	41.786	-2.4	85.3	-0.15	0.879
FAMSIZE	Unmatched	6.068	5.962	4.4		0.29	0.768
	Matched	6.028	6.025	0.1	97.3	0.01	0.994
LANDHOLD	Unmatched	1.986	1.917	4.4		0.29	0.768
	Matched	1.985	1.913	4.6	-4.6	0.27	0.784
CHCKFEXP	Unmatched	20.108	21.245	-11.3		-0.74	0.459
	Matched	20.521	19.555	9.6	15.0	0.60	0.547
TECHEXPI	Unmatched	0.547	0.514	6.7		0.44	0.658
	Matched	0.521	0.482	7.9	17.2	0.47	0.641
FRETECH	Unmatched	0.770	0.623	32.3		2.11*	0.036
	Matched	0.761	0.744	3.7	88.6	0.23	0.817
EXTSERVI	Unmatched	0.689	0.406	59.1		3.88***	0.000
	Matched	0.676	0.676	0.0	100.0	0.00	1.000
HLTHSERV	Unmatched	0.284	0.245	8.7		0.58	0.565
	Matched	0.282	0.296	-3.2	63.4	-0.18	0.854
TRAINING	Unmatched	0.721	0.500	48.3		3.16***	0.002
	Matched	0.718	0.707	2.4	95.1	0.15	0.883
MARKETDS	Unmatched	11.291	12.276	-14.0		-0.92	0.356
	Matched	11.535	11.300	3.4	76.1	0.20	0.840

***=P≤0.001, * =P≤0.05

3.2.5 Estimation of the average treatment effects (ATT)

The average treatment effect on treated due to improved chicken breeds adoption (CHICKADO) on the outcome variables is indicated on Table 4. As shown, adopters and non-adopters show 73.2% and 72.7% knowledge and skill improvement due to the technology intervention but adoption didn't bring significant difference on knowledge and skill (KNOWSKIL) improvement between the adopters and non-adopters. However, technology adoption had significant (P<0.001) impact on adopters as benefited from the technology (BENEFITD), changes on the livelihood of the household (LIVEHOOD), changes on egg production (CHANGEGG), egg consumption (EGGCONS) and income change (INCOME) as impact indicators. Adopters were significantly benefited from the technology by 68.5% (difference value/adopters value*100) as compared to non-adopters. Moreover, due to adopting the technology, adopters could produce 101 more eggs per layer/year, consumed 18 more eggs/year and got 168.65 Birr more income per layer/year as compared to non-adopters. The ATT and the overall average treatment effect (ATE) on the study population are indicated in Table 5. As shown in the Table, the ATE of improved chicken breeds intervention on the population increased knowledge and skill by 3.6%, egg production by 97.4 eggs per layer/year, egg consumption by17.2 eggs/household per year and income by 163.05 Birr/layer/year.

Table 4. The ATT of improved chicken breeds intervention on the outcome indicators

Treatment	Outcome	Adopters	Non-adopters	Difference	$S.E.^{bs}$	T-stat
CHICKADO	KNOWSKIL	0.732	0.727	0.006	0.076	0.07
	BENEFITD	0.958	0.301	0.656	0.126	10.62***
	LIVEHOOD	0.831	0.079	0.752	0.066	12.86***
	CHANGEGG	157.87	56.57	101.30	7.92	15.42***
	EGGCONS	38.04	19.91	18.13	2.81	6.61***
	INCOME	249.74	81.09	168.65	24.18	12.04***

****=P≤0.001; ^{bs} bootstrapped S.E. obtained for 100 replications*

Table 5. Unmatched and matched average treatment effect of outcome variables

Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
knowskil	Unmatched	.743243243	.547169811	.196073432	.072155868	2.72
	ATT	.732394366	.726760563	.005633803	.084941169	0.07
	ATU	.591836735	.648979592	.057142857	.	.
	ATE			.035502959	.	.
Benefitd	Unmatched	.959459459	.198113208	.761346252	.050418382	15.10
	ATT	.957746479	.301408451	.656338028	.06178963	10.62
	ATU	.204081633	.955102041	.751020408	.	.
	ATE			.711242604	.	.
Livehood	Unmatched	.837837838	.075471698	.76236614	.047430605	16.07
	ATT	.830985915	.078873239	.752112676	.05848412	12.86
	ATU	.071428571	.797959184	.726530612	.	.
	ATE			.737278107	.	.
Changegg	Unmatched	156.337838	57.0377358	99.300102	5.59746435	17.74
	ATT	157.873239	56.5690141	101.304225	6.56757751	15.42
	ATU	57.4081633	152.004082	94.5959184	.	.
	ATE			97.4142012	.	.
Eggcons	Unmatched	38.0405405	19.0188679	19.0216726	2.24241873	8.48
	ATT	38.0422535	19.9098592	18.1323944	2.74472829	6.61
	ATU	19	35.5510204	16.5510204	.	.
	ATE			17.2153846	.	.
Icome	Unmatched	245.359459	73.2853774	172.074082	11.4022165	15.09
	ATT	249.740141	81.0860563	168.654085	14.0134593	12.04
	ATU	74.1841837	233.166122	158.981939	.	.
	ATE			163.045385	.	.

3.2.6 Sensitivity analysis

Table 6 shows the result of Rosenbaum sensitivity test for upper bound significance level of improved chicken breed technology participation on outcome variables. Each column shows the critical value of Γ which bears statistical difference between treated and control households. As shown in Table, when Γ = 1 (assuming of no hidden bias due to an unobserved confounder), the sensitivity analysis estimated p-values were quite close to estimated p-values (***=p<0.001) of the matching analysis of Table 4. When Γ value increases by 0.5 to Γ=3, the p-values changes were significant which was below 0.05 (usual threshold).

Table 6. Rosenbaum sensitivity test for upper bound significance level (N = 180 matched pairs)

	Γ(Gamma)				
Outcome variable	Γ =1	Γ =1.5	Γ =2	Γ =2.5	Γ =3
BENEFITD	0.000	2.4e-15	5.9e-12	6.5e-10	1.5e-08
LIVEHOOD	0.000	4.2e-12	1.6e-09	6.1e-08	6.8e-07
CHANGEGG	0.000	0.000	1.1e-16	8.8e-14	8.9e-12
EGGCONS	0.000	0.000	2.2e-16	1.5e-13	1.4e-11
INCOME	0.000	0.000	1.1e-16	9.5e-14	9.4e-12

Γ = log odds of differential due to unobserved factors; 1, 1.5....and 3 are measures of the degree of departure from random assignment of treatment.

Table 7 shows the upper bound Hodges-Lehmman point estimates. Since the lower bounds under underestimated the true treatment effect, upper bound Hodges-Lehmman point estimates were used. As shown in the Table, the median estimates were smaller than the mean estimates differences reported in Table 4. However, except the impact of the treatment on the livelihood changes of the participants, the estimates were slightly more robust and the upper bounds didn't bracket zero. The Hodges-Lehmman point estimates of livelihood changes smaller than the estimated mean difference in Table 4 and shows slightly more robust as Γ value of 1.5 before the upper bound brackets zero. If there is no hidden bias, Hodges-Lehmman point estimates was 0.50, however, as Γ value increases more than 1.5, the estimated upper bounds bracket zero that implies there was possible hidden bias due to an unobserved confounder on LIVEHOOD.

Table 7. Rosenbaum upper bound sensitivity test for Hodges-Lehmann point estimate

Outcome variable	Γ(Gamma)				
	Γ =1	Γ =1.5	Γ =2	Γ =2.5	Γ =3
BENEFITD	0.50	0.50	0.50	0.50	0.50
LIVEHOOD	0.50	0.50	-3.7e-07	-3.7e-07	-3.7e-07
CHANGEGG	95	77.5	65	60	57.5
EGGCONS	25	23	22	20	19
INCOME	130	107.8	94.5	85.75	79

**Hodges-Lehmann point estimates are upper bound estimates; Γ = log odds of differential due to unobserved factors; 1, 1.5....and 3 are measures of the degree of departure from random assignment of treatment.*

4. Discussion

The estimated model pseudo-R^2 of the current study was fairly low (0.1108). This indicates the covariates were well fitted with the model. In agreement, Caliendo & Kopeinig (2008) and Pradhan & Rawlings (2002) revealed that low pseudo-R^2 value indicates that the allocation of the treatment has been fairly random and the result suggests that treatment households do not have diverse characteristics over all and hence obtaining a good match between treatment and control households. The coefficient of pscore estimated for age, chicken keeping experience and market distance show negative values. These indicate, older farmers were reluctant to participate on the technology, more chicken keeping experience doesn't mean farmers could participate on the technology and as market become distance from the farmers homestead, the likelihood of their participation on the technology become less. Participation on improved chicken breed technology was positively and significantly influenced by extension and training services. These imply, as the respondents get better extension and training services, the probability their participation on improved chicken breed technology increases too. The logit estimated intercept of the current study was negative and insignificant. This indicates more of the covariates less likely influenced the overall population to participate on technology.

Before matching some covariates (27.8%) estimated pscores show significant but after matching all covariate pscores show insignificant. This indicates, there was no distribution difference between adopters and non-adopters after the pscores were matched. In agreement, after matching there should be no systematic differences in the distribution of covariates between both groups (Caliendo & Kopeinig 2008). In the current study, after matching mean standardized bias (SB) reduction ranged from 0.1-9.6% which was fairly below the critical level of 20% suggested by Rosenbaum and Rubin (1985). Moreover, very low Pseudo-R^2 (0.008) after matching agreed with the report of Borga (2011) and Tolemariam (2010), after matching the pseudo-R^2 is fairly low implying households do not have much distinct characteristics overall and a good match between treated and non-treated households. Therefore, the current study matching had high degree of covariate balance that shows similar observed characteristics between the adopter and non-adopter groups to use in the estimation procedures.

The average treatment effect due to improved chicken breeds intervention on the outcome variables results show indispensably significant impact on participants. Positive values of ATT difference (adopter value minus non-adopter value) indicate that the participants have been benefited from the intervention. Even though, the t-test didn't show significant on knowledge and skill, both groups show an improvement. This implies that technology intervention benefited both the adopters and non-adopters on knowledge and skill improvement. Adopters were significantly benefited from the technology as compared to non-adopters. Moreover, adopters could able to produce more eggs per layer/year, consumed more eggs/year and got better income per layer/year as compared to non-adopters. In lined with, Dehinenet *et al.* (2014) reported that dairy technology adopters significantly consumed more milk, sold more milk and can get better income per annum as compared to the non-adopters. Moreover, Tolemariam (2010) reported that the quantity of cotton meal used as feed supplements for sheep fattening brings significant impact on treated households as compared to control households and market oriented impact on number of sheep fattened.

Knowledge and skill improvement t-test between adopters and non-adopters shows insignificant, due to this it was not considered in the sensitivity analysis of this study. In agreement, Hujer *et al.* (2004) reported that, sensitivity analysis for insignificant ATT effects is not meaningful and therefore not considered. For significant outcome variables the sensitivity analysis p-values show similar significance test as compared to before sensitivity analysis. The upper bound p-values were used to see changes in p-values. As Γ (gamma) value increased by 0.5 to Γ=3, the p-values showed significant which was below 0.05. This indicates, adopters and non-adopters were correctly matched and there were no differences between the two groups (no hidden bias due to an unobserved confounder). Further it indicates that important covariates that affected both participation and outcome variables were considered. According to Keele (2010), p-value is valid if there are no unobserved confounders between the treated and control groups and data are correctly matched with no differences.

In the current study, since the lower bounds Hodges-Lehmman point estimates under underestimated the true treatment effect, upper bound were used. In agreement, Becker and Caliendo (2007) and Keele (2010) revealed that the lower bounds estimates under the assumption of true treatment effect were underestimated and less important to be reported. The Hodges-Lehmman point estimates of livelihood changes smaller than the estimated mean difference and shows slightly more robust as Γ value of 1.5 before the upper bound brackets zero. If there was no hidden bias, Hodges-Lehmman point estimates was 0.50, however, as Γ value increased more than 1.5, the estimated upper bounds bracket zero that implies there was possible hidden bias due to an unobserved confounder on the livelihood changes. In agreement, Diprete & Gangl (2004) reported that, if sensitivity analysis gamma value is lowest and encompasses zero, the probability of an unobserved characteristic is relatively high and the estimated impact is therefore sensitive to the existence of unobservable.

5. Conclusion

Adopters were significantly benefited from the technology as compared to non-adopters. Adopters could able to produce more eggs per layer/ year, consumed more eggs/year and got 168.65 Birr more income per layer/year as compared to non-adopters. Improved chicken breeds intervention had positive ATE. In sensitivity analysis, Hodges-Lehmman point estimate shows there was possible hidden bias due to an unobserved confounder on the livelihood change. Except livelihood changes, the significant difference of adopters and non-adopters on outcome variables was due to the treatment effect of technology intervention.

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