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*Full Length Research Paper*

# The impact of dairy technology adoption on small holder dairy farmers livelihoods in selected zones of Amhara and Oromia National Regional States, Ethiopia

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Abstract

**This study was carried out in two National Regional States (Amhara and Oromia) in Ethiopia using propensity score matching model. Tota1ly, 384(equal proportion of adopters and non-adopters) smallholder farmers were selected for the study. However, 163 and 167 adopter and non adopter smallholder farmers were selected by the model for impact analysis, respectively. Both milk consumed per day at farm level and destined to the market were higher in dairy technology adopter households than control groups (non-adopters). Adopter smallholder farmers also could get more income from milk production on average than the non-adopter smallholder farmers. Introducing different dairy technologies and a sustainable supply of cross breed heifers/cows with the reasonable cost should be supported with a continuous training or technical backup.**

**Keywords:** Adopters, income, milk consumption, non-adopters, and propensity score matching

## INTRODUCTION

In spite of the large livestock population, the contribution of the Ethiopian livestock sector in general and the dairy sector in particular is below its potential at both the national and household level (Berhanu et al., 2007). This low production level of the sector is attributed to inefficient productivity of the livestock as a result of the traditional method of production, poor breeds, poor feeding, inferior health care and services, and low capital investment in human and fixed assets.

According to the central statistical agency estimation (CSA, 2011), the total cow milk production (excluding milk suckled) for the rural sedentary areas of the country during the reference period, is about 4.06 billion liters, average lactation period per cow during the reference period at country level was estimated to be about six months and average milk yield per cow per day was about 1.85 liters. In Ethiopia, dairy production is mainly of subsistent type largely based on indigenous breeds of cattle. Milk production from this system is low to support the demand for the continuously increasing human population, particularly in urban centers (Azage and Alemu , 1998). Hence to increase production and productivity the sector; introducing improved methods of fodder production for dairy cattle, supplying of crossbred heifer, establishing of farmer based bull stations, delivering of pure-bred Friesian and Jersey breeding bulls to villages, providing of animal health service in the villages, assisting in marketing the surplus milk by the establishment of farmers' milk marketing units and the establishment of wells and watering points to villages

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were done in the study area by SDDP ( Smallholder Dairy Development Project ) in 1995 (Reijo, 1998). Since then different dairy technologies has been transferred through both governmental, NGOs and private sectors.

Even though large efforts have been made to disseminate dairy technologies through the support of governmental and non-governmental organizations in different parts of the country including the study area, the rate of adoption of dairy technologies by farm households varies widely across different agro-ecologies and within the same agro-ecology based on various technical and non-technical factors. Accordingly, the contribution and benefits of dairy technologies differ among farm households. On the other hand, for policy design and effective management of extension programmes, information on the impact of dairy technology on the livelihoods of smallholder farmers is very important and would help to come up with workable recommendations to improve the performance of the sector. Therefore, this study was aimed to determining the impact of dairy technology adoption on smallholder household livelihoods.

## Theoretical Framework

Impact evaluations rely on econometric and statistical models. There are three main kinds of impact evaluation designs. These are experimental, quasi-experimental and non-experimental with which are respectively associated with control groups, comparison groups, and non-participants. Impact Evaluation (IE) rigorously measures the impact that a project has on beneficiaries. It typically does this by comparing outcomes between beneficiaries and a control group (AIEI, 2010). Since the data for this study were obtained from survey, non-experimental impact evaluation design was preferred and analyzed using Propensity Scores Matching (PSM).

Propensity score matching is a non-experimental method for estimating the average effect of social programs (Rosenbaum and Rubin 1983; Heckman et al., 1998). The method compares average outcomes of participants and non-participants, conditioning on the propensity score value. The parameter of interest is the average treatment effect and has focused on strong identification conditions.

In order to make causal inferences, random selection of subjects and random allocation of the treatment to subjects is required. In observational studies random assignment to treatments is impossible. The primary limitation of an observational study is that there may be random selection of subjects but not random allocation of treatments to subjects. When there is a lack of randomization, casual inferences cannot be made because it is not possible to determine whether the difference in outcome between the treated and control (untreated) subjects is due to the treatment or differences between subjects on other characteristics. Subjects with certain characteristics may be more likely to receive treatment than others.

In the estimation of average treatment effect using propensity score matching method there are different steps to be followed. First the propensity score is estimated using a choice model. To estimate the participation probability, logit model estimated using a maximum likelihood method Etimation (MLE) is often preferred due to the consistency of parameter estimation associated with the assumption that error term *v* in the equation has a logistic distribution (Ravallion, 2001). In the second step matching algorithm is selected based on the data at hand after undertaking matching quality test. In the third stage overlap condition or common support condition is identified. In the fourth stage the treatment effect is estimated based on the matching estimator selected on the common support region (Owusu and Awudu, 2009).

## MATERIALS AND METHODS

### Study Area Description

This study was carried out in two National Regional States (Amhara and Oromia). Amhara National Regional State (ANRS) is located in the north-western part of the country which is found between 90-130 45''North Latitude and 350-400 30''East longitude. The total area of the region is approximately 170,752 Sq.Km whereas Oromia National Regional State (ONRS) lies in the central part of the country with larger protrusions towards the south and west directions. It has an area of 353,690 $km^2$ (OPEDB, 2000).The region has 17 administrative zones and 251 districts. Totally, six cooperative centers namely *Shemeshengo* and *Yetenora* from ANRS and *Godino, Babogaya, Debretsigie* and *Torbenashie* from ONRS were selected.

Sampling Procedure and Sample Size

Multistage sampling procedure was used to select farm households for this study. During the first stage, study Regions (Oromia and Amhara) were selected purposively based on dairy technology adoption which was delivered by SDDP (Smallholder Dairy Development Programme), milk production potential and number of crossbred cows distributed. During the second stage, one zone from Amhara National Region State (East Gojjam Zone) and two zones from Oromia National Regional State (North Showa and East Showa zones) were selected based on the dairy potential of the area. During the third stage, six cooperative center areas (two from each zone) were selected randomly from others. During fourth stage, farm households in the selected sites were categorized into dairy technology adopters and non-adopters and then 384 smallholder farmers were selected by systematic random sampling by considering the proportionality of the number of farm households in each cooperative center areas.

These total sample size (384 smallholder farmers) were determined according to the following formula at 95%

confidence Interval (Fox et al., 2007). Prior to farm household sampling, an initial complete listing (census) of all the farm households in the selected area was obtained from *Woreda* Agriculture and Rural Development Office.

$N = P\,(100\% - P)/\,(SE)^2$; $SE = MRE/1.96$

Where;

**N**= Sample size; **P**= Proportion of dairy technology adopter smallholder farmers; **SE** = Standard error; **MRE** = Margin for random error (5%) and 1.96 is tabular value for 95% confidence interval.

**Data collection**

Primary data were collected through personal interviews by trained enumerators using a pre-tested semi-structured survey questionnaire from respondents who has at least one lactating cow at the time of survey. The questionnaire was used to collect information on milk production, milk consumption, milk sold and income; farmer-household socio-economic characteristics; technical, institutional and environmental points. The socio-economic characteristics include the following amongst others: farmers' age, gender, educational status, land size, farm experience, off-farm income and family size.

**Statistical Analysis**

**Analytical Model**

The hypothesis was that adopting dairy technology has a positive impact on the smallholder livelihoods which was measured by different livelihood impact indicators (availability of animal origin food for household consumption (AAOFHC), total milk consumed per day at farm level (TMCPDAFL), total milk sold per annum in liter (TMSPA), total income from milk and milk products (TIMMP), allow to send children to school (ASCS), allow to hire labor for agricultural activities (AHLAA) and allow to built new or renovate the existing family house (ABNFH). In this case decision making on dairy technology adoption was a binary exogenous variables.

**Variable Definition and Hypotheses**

The data were cover information necessary to make farm level indices of social-economic characteristics, factors of dairy technology adoption and its impact on the household livelihood in the study area. Both continuous and discrete variables were used on economic theories and findings of different empirical studies. Accordingly, in order to investigate the research questions of this study, the following variables were constructed.

**Dependent variables:** A bundle or package of different technological elements such as forage seed, bull service, AI services, and veterinary services, feed supply and crossbred heifer (CB) was transferred to smallholder farmers. For the household who adopts dairy technology the variable takes the value of one where as it takes the value of zero for the household who does not adopt. However, cross breed heifer/cattle adoption was taken as a proxy for this study.

**Impact of Dairy Technology Adoption (IDTA):** it can be a dummy variable that represents the probability of the household that can be benefited from dairy technology or not. Those benefits or impact indicators that were examined include availability of animal origin food for household consumption (AAOFHC), total milk consumed per day at farm level (TMCPDAFL), total milk sold per annum in liter (TMSPA), total income from milk and milk products (TIMMP), allow to send children to school (ASCS), allow to hire labor for agricultural activities (AHLAA) and allow to built new or renovate the existing family house (ABNFH).

**Independent (Explanatory) Variables:** Independent variables are variables that stand alone and are not changed by the other variables but cause change in Dependent Variable/s. some of the independent variables used in this study were described as follow.

**Sex of the household head (GENDER):** This was a dummy variable that took a value of one if the household head was male and zero otherwise. Gender was expected to affect dairy technology adoption. Male farmer heads were expected to adopt dairy technology more than female headed. Male farmers had more access and exposure to get the information about the dairy technology and they were making decision to adopt than what female farmers were doing.

**Family size (FS):** It is a continuous variable. As dairying was/is labor intensive: dairy production, in general and marketable surplus of dairy products in particular, is a function of labor. Accordingly, household with more family members tended to have more labor and to adopt dairy technology than household with less family members which in turn increased milk production and then milk market participation of the households.

**Distance to Market Center (DMC):** Is location of the farm household from the nearest milk market and was measured in kilometer**.** Distance to market center was expected to affect the dairy technology adoption. The farthest the market distance the least the dairy technology could be happened because the closer the milk market to farm household, the lesser would be the transportation charges and loss due to spoilage, and better access to market information and facilities. This improved return to labor and capital; increased farm-gate price and incentive to participate in dairy technology adoption.

**Distance from Agricultural Development Center (DADC):** It is a continuous variable and measured in kilometer. Distance from agricultural development center was expected to affect the dairy technology adoption. The Agricultural Development Center (ADC) was/ is usually strategically located within the farming areas and it is the place where the local extension worker was/is stationed. As distance from the agricultural development center (DADC) increases, livestock technology adoption decreases because this causes transport cost incurred in obtaining information on technologies and inputs to increase. Farmers were/are less likely to adopt the livestock technologies as the distance increases from the ADC.

**Education Level of the Household Head (ELHH):** It was a dummy variable that took a value of one if the household head was educated and zero otherwise. Education plays an important role in the adoption of innovations/new dairy technologies. Further, education was/is believed to improve the readiness of the household to accept new ideas and innovations, and get updated demand and supply price information which in turn enhances producers' willingness to produce more and increase milk market entry decision and volume of sale. Therefore, the more educated the household head, the higher the likelihood to decide for dairy technology adoption.

**Age of the Household Head (AHH):** It is a continuous variable and measured in years. AHH also was expected to affect the dairy technology adoption. It was hypothesized that there was/is an indirect relationship between age of household heads and dairy technology adoption. As the age of the household head increased, the probability of adoption decreased because they were/are inactive to participate in the new technology dissemination process, most likely due to being more influenced by culture.

**Off-farm activity participation (OFAP):** It is a dummy variable that took a value of one if the household head participated in an off-farm activity and zero otherwise. OFAP was/is expected to affect dairy technology adoption. A household head farmer who has an access to off-farm employment has a positive effect on adoption of dairy technologies. This entails that increased access to off-farm employment can lead to increased adoption of dairy technologies. One explanation for this result was/is that income from off-farm activities provides supplemental income to finance technology expenditures, for example: purchase of salt block, urea, mineral lick, hay and small tools for dehorning and castration and even to the extent of buying crossbred heifers.

**Land holding (LH):** It is a continuous variable and measured in hectares. It was hypothesized that there was/is a direct relationship between the size of land held by farm households and dairy technology adoption. Farmers with less land were expected not to be willing to adopt a dairy technology since they were thinking that the technology needs more land for forage production.

**Access to credit service (ACS):** Access to credit was measured as a dummy variable taking a value of one if the household has access to credit and zero otherwise. This variable was/is expected to influence the dairy technology adoption because of the very high initial investment cost which households may not afford easily. Credit relaxes the financial constraint of the household to invest on dairying.

**Access to Dairy Production Extension Service (ADPES).** This variable was measured as a dummy variable taking a value of one if the farm household had access to dairy production extension service and zero otherwise. It was/is expected that ADPES affect dairy technology adoption. A household head who had/has access to dairy production extension service was/is more prone for technology adoption than those who had/ has no access. Extension service widens the household's knowledge with regard to the use of improved dairy production technologies which leads to adopt more.

**Farming experience**: It is a continuous variable and measured in years. It refers to the number of years that the smallholder farmer practiced farming activity after the dairy technology transferred to the area. It was hypothesized that there was/is a direct relationship between the farming experience and dairy technology adoption. Farmers with high farming experience were expected to be willing to adopt a dairy technology since they were getting information about the advantages of dairy technology through different ways.

Propensity score matching (PSM) constructs a statistical comparison group that is based on a model of the probability of participating in the treatment, using observed characteristics. Participants are then matched on the basis of this probability, or *propensity score*, to nonparticipants. The average treatment effect of the program is then calculated as the mean difference in outcomes across these two groups. The validity of PSM depends on two conditions: (a) conditional independence (meaning that unobserved factors do not affect participation) and (b) sizable common support or overlap in propensity scores across the participant and nonparticipant samples (Khandker et al., 2010).

The first step in PSM was to determine the propensity score and satisfy the balancing property. It was done using the "pscore" command in Stata. After obtaining the predicted probability values conditional on the observable covariates (the propensity scores) from the binary estimation, matching was done using a matching algorithm that was selected based on the data at hand.

Even though different approaches were used to match adopters and non-adopters on the basis of the propensity score, choice of matching estimator was decided based on the balancing qualities of the estimators. According to (Dehejia and Wahba, 2002), the final choice of a matching estimator was guided by different criteria such as equal means test referred to as the balancing test, pseudo-$R^2$ and matched sample size. Balancing test is a test conducted to know whether there is statistically significant difference in mean value of per-treatment characteristics of the two groups of the respondents and preferred when there is no significant difference. Accordingly, matching estimators were evaluated via matching the adopters and non-adopters households in common support region. Therefore, a matching estimator having balanced (insignificant mean differences in all explanatory variables) mean, bears a low pseudo-$R^2$ value and also the one that results in large matched sample size was preferred (Alemu, 2010). Then the effect of household's participation in dairy technology adoption on a given outcome (availability of animal origin food for household consumption, total milk consumed per day at farm level, total milk sold per annum in liter, total income from milk and milk products, allow to send children to school, allow to hire labor for agricultural activities and allow to built new or renovate the existing family house) (Y) was specified as:

$\tau_i = Y_i(D_i = 1) - Y_i(D_i = 0)$……………………………………………….equ.1

Where $\tau_i$ was treatment effect (effect due to adoption of dairy technology), $Y_i$ was the outcome on household head i, $D_i$ whether household head i had got the treatment or not (i.e., a household head adopt dairy technology or not). However, one should note that $Y_i$ ($D_i$ = 1) and $Y_i$ ($D_i$ =0) cannot be observed on the same household head at the same time. Depending on the position of household head in the treatment (adoption), either $Y_i$ ($D_i$ = 1) or $Y_i$ ($D_i$ =0) was unobserved outcome (called counterfactual outcome). Due to this fact, estimating individual treatment effect $\tau_i$ was not possible and one had to shift to estimating the average treatment effects of the population than the individual one. Most commonly used average treatment effect estimation was the average treatment effect on the treated ($\tau_{ATT}$), and specified as:

$\tau_{ATT} = E(\tau \mid D = 1) = E[Y(1) \mid D = 1] - E[Y(0) \mid D = 1]$……………………..equ.2

As the counterfactual mean for those being treated, $E[Y(0) \mid D = 1]$ was not observed, one had to choose a proper substitute for it in order to estimate the average treatment effect (ATT). One might have thought to use the mean outcome of the untreated individuals, $E[Y(0) \mid D = 0]$ as a substitute to the counterfactual mean for those being treated, $E[Y(0) \mid D = 1]$.

In this particular case, variables that determined household's decision to participate in the dairy technology adoption might have also affected availability of animal origin food for household consumption, total milk consumed per day at farm level, total milk sold per annum in liter, total income from milk and milk products, allow to send children to school, allow to hire labor for agricultural activities and allow to built new or renovate the existing family house. Therefore, the outcomes of individuals from treatment and comparison group would have differed even in the absence of treatment leading to a self-selection bias.

By rearranging, and subtracting $E[Y(0) \mid D = 0]$ from both sides, one can get the following specification for ATT.

$E[Y(1) \mid D = 1] - E[Y(0) \mid D = 0] = \tau_{ATT} + E[Y(0) \mid D = 1] - E[Y(0) \mid D = 0]$….equ.3

Both terms in the left hand side are observables and ATT can be identified, if and only if $E[Y(0) \mid D = 1] - E[Y(0) \mid D = 0] = 0$. i.e., when there is no self-selection bias. This condition can be ensured only in social experiments where treatments are assigned to units randomly (i.e., when there is no self-selection bias). In non-experimental studies one has to introduce some identifying assumptions to solve the selection problem. The following were two strong assumptions to solve the selection problem.

**Conditional Independence Assumption**

Given a set of observable covariates (X) which were not affected by treatment (adoption participation), potential outcomes (household income, number of hired laborers employed; availability of animal source food at house hold level; rate of sending children to school; and to build new or renovate the existing family house) were independent of treatment assignment (independent of how adoption participation decision was made by the household).This assumption implied that the selection was solely based on observable characteristics, and variables that influence treatment assignment (adoption participation decision was made by the household) and potential outcomes (household income, number of hired laborers employed; availability of animal source food at house hold level; rate of sending children to school; and to build new or renovate the existing family house) were simultaneously observed.

**Common support**

This assumption ruled out perfect predictability of D given X. That was

$0 < P(D = 1 \mid X) < 1$

This assumption ensured that persons with the same X values had a positive probability of being both participants and non-participants.

Given the above two assumptions, the PSM estimator of ATT was written as:

$\tau^{PSM}_{ATT} = E_{P(X) \mid D=1}\{E[Y(1) \mid D = 1, P(X)] - E[Y(0) \mid D = 0, P(X)\}$……equ.4

Where P(X) was the propensity score computed on the

**Table 1:** Variance Inflation Factor (VIF) for explanatory variables

| Variable definition | Variables` symbols | VIF | 1/VIF |
|---|---|---|---|
| Farming experience (Years) | FE | 3.43 | 0.29 |
| Age of the household head (years) | AHH | 3.10 | 0.32 |
| Total cattle in TLU(Tropical Livestock Unit) | TCTLU | 1.84 | 0.54 |
| Total land holding (hector) | LH | 1.75 | 0.57 |
| Total income from milk and milk products per year (Birr) | TIMMP | 1.58 | 0.63 |
| Have you used credit service intuitions? (0 = no, 1= yes) | UCS | 1.51 | 0.66 |
| Is cross breed cattle availably?(0 = no, 1= yes) | CBCA | 1.40 | 0.72 |
| Educational status (0 = non-educated, 1= educated) | ELHH | 1.38 | 0.72 |
| Have you used saving service intuitions? (0 = no, 1= yes) | USS | 1.35 | 0.74 |
| Family size (number) | FS | 1.30 | 0.77 |
| Distance from Agricultural Development Center (kms) | DADC | 1.30 | 0.77 |
| Off-farm activity participation(0 = not accessible, 1 = accessible) | OFAP | 1.29 | 0.77 |
| Are extension services on livestock available? (0 = no, 1= yes) | ADPES | 1.28 | 0.79 |
| Gender of the household head(0= female, 1= male) | GENDER | 1.24 | 0.80 |
| Availability training services on livestock? (0 = no, 1= yes) | ATL | 1.19 | 0.84 |
| Availability of veterinarian /animal health service services? (0 = no, 1= yes) | AVS | 1.14 | 0.88 |
| | Mean VIF | 1.63 | |

**Table 1:** Propensity score estimation

| variable | coefficient | Std. Err. | Z-value |
|---|---|---|---|
| GENDER | -0.018 | 0.180 | -0.10 |
| AHH | -0.0004 | 0.007 | -0.06 |
| FS | 0.068 | 0.037 | 1.84* |
| ELHH | 0.201 | 0.172 | 1.17 |
| DADC | -0.080 | 0.022 | -3.58*** |
| ADPES | 0.705 | 0.180 | 3.91*** |
| AVS | 0.018 | 0.330 | 0.05 |
| ATL | 0.800 | 0.162 | 4.90*** |
| USS | 0.723 | 0.171 | 4.22*** |
| UCS | 0.035 | 0.194 | 0.18 |
| CBCA | 0.761 | 0.187 | 4.08*** |
| TCTLU | 0.100 | 0.034 | 2.91*** |
| constant | -2.277 | 0.532 | -4.28*** |
| Number of observation | 384 | | |
| LR $chi^2(12)$ | 161.62 | | |
| Prob > $chi^2$ | 0.000 | | |
| Pseudo $R^2$ | 0.3036 | | |
| Log likelihood | -185.35625 | | |

*** and * indicate statistical significance at 1% and 10%, respectively.
**Source**: Researcher own organized

covariates X and the PSM estimator was the mean difference in outcomes over the common support, appropriately weighted by the propensity score distribution of participants.

## RESULTS

The basic idea behind PSM was to match each adopter with an identical non adopter and then measure the average difference in the outcome variable between the adopters and the non-adopters. In order to use PSM model, two strong assumptions namely Conditional Independence Assumption (CIA) and communal support where taken to alleviate selection problems and the following three procedures were practiced. i) Estimated the propensity score; ii) Choosed a matching algorithm that used the estimated propensity scores to match untreated units to treated units and iii) Estimated the impact of the intervention with the matched sample and calculated standard errors was discussed. Hence, the balanced propensity scores and then a best fit matching estimator to the data were used. Lastly, based on those propensity scores estimated and matching estimator selected, matching between adopters and non-adopters was done to find out the average treatment effect on the treated (ATT) for intended outcome variables.

Prior to estimate propensity scores, the explanatory variables were checked for existence of multicollinearity and hetroscedasticity problem with appropriate technique as it is indicated in Table 1.

**Table 3:** Performance measure of matching estimators at the study areas

| Matching estimator | Performance Criteria | | |
|---|---|---|---|
| | Balancing test | Pseoudi-$R^2$ | Matched sample size |
| **NN** | | | |
| NN(1) | 5 | 0.239 | 330 |
| NN(2) | 5 | 0.236 | 330 |
| NN(3) | 5 | 0.222 | 330 |
| NN(4) | 5 | 0.215 | 330 |
| NN(5) | 5 | 0.211 | 330 |
| **Radius caliper** | | | |
| 0.01 | 5 | 0.164 | 279 |
| 0.25 | 5 | 0.239 | 330 |
| 0.50 | 5 | 0.239 | 330 |
| **Kernel matching(KM)** | | | |
| Band width 0.1 | 5 | 0.191 | 330 |
| Band width 0.25 | 5 | 0.127 | 330 |
| Band width 0.5 | 5 | 0.008 | 330 |

* Number of explanatory variables with no statistically significant mean differences between the matched groups of adopter and non-adopter households.

**Table 4:** Testing of covariates` balance

| Variables | Unmatched Matched | Mean Treated | % bias Control | % reduction /bias/ | T- test | T | P>/t/ |
|---|---|---|---|---|---|---|---|
| GENDER | Unmatched | 0.739 | 0.708 | 7.0 | | 0.68 | 0.495 |
| | Matched | 0.712 | 0.729 | -3.8 | 45.5 | -0.00 | 0.996 |
| AHH | Unmatched | 46.068 | 45.672 | 3.2 | | 0.32 | 0.752 |
| | Matched | 45.552 | 45.961 | -3.3 | -3.3 | -0.38 | 0.703 |
| FS | Unmatched | 6.542 | 5.667 | 39.3 | | 3.85*** | 0.000 |
| | Matched | 6.239 | 5.919 | 14.4 | 63.3 | -0.25 | 0.806 |
| ELHH | Unmatched | 0.630 | 0.438 | 39.3 | | 3.85*** | 0.000 |
| | Matched | 0.619 | 0.523 | 19.7 | 49.7 | 0.03 | 0.980 |
| DADC | Unmatched | 4.239 | 5.428 | -32.9 | | -3.22*** | 0.001 |
| | Matched | 4.476 | 4.696 | -6.1 | 81.5 | 0.29 | 0.773 |
| ADPES | Unmatched | 0.786 | 0.536 | 54.6 | | 5.35*** | 0.000 |
| | Matched | 0.748 | 0.686 | 13.8 | 74.8 | -0.33 | 0.741 |
| AVS | Unmatched | 0.948 | 0.927 | 8.6 | | 0.84 | 0.400 |
| | Matched | 0.945 | 0.945 | -0.1 | 98.3 | -0.26 | 0.794 |
| ATL | Unmatched | 0.542 | 0.219 | 70.4 | | 6.89*** | 0.000 |
| | Matched | 0.496 | 0.401 | 20.8 | 70.4 | -0.64 | 0.526 |
| USS | Unmatched | 0.641 | 0.307 | 70.6 | | 6.92*** | 0.000 |
| | Matched | 0.601 | 0.423 | 37.8 | 46.5 | -0.50 | 0.616 |
| UCS | Unmatched | 0.406 | 0.281 | 26.5 | | 2.59** | 0.010 |
| | Matched | 0.393 | 0.409 | -3.6 | 86.4 | -0.40 | 0.692 |
| CBCA | Unmatched | 0.844 | 0.547 | 68.0 | | 6.66*** | 0.000 |
| | Matched | 0.816 | 0.746 | 16.0 | 76.4 | -0.79 | 0.432 |
| TCTLU | Unmatched | 5.715 | 4.544 | 45.6 | | 4.46*** | 0.000 |
| | Matched | 5.157 | 5.102 | 2.1 | 95.3 | -0.56 | 0.577 |

% reduction /bias/= ((unmatched % bias – /matched % bias/)/ unmatched % bias)*100

### Propensity Score Estimation

The first step in PSM was to determine the propensity score and satisfy the balancing property and it was done using the "pscore" command in Stata. Accordingly, twelve explanatory variables (Table 2) were identified after iteration to fulfill the criteria of "the balancing propensity is satisfied".

### Choice of Matching Algorithm

Matching estimators were evaluated via matching the adopters and non-adopters households in common support region. Hence, based on the matching quality indicators, kernel matching with band width of 0.5 resulted in relatively low pseudo-$R^2$ with best balancing test (all explanatory variables insignificant) and large matched sample size as compared to other alternative matching estimators as indicated in Table 3.

**Table 5:** Estimates of average treatment effect (ATT) on production indicators

| Intervention | Variables | Treated (Adopters) | Control (Non-adopters) | Difference | S.E.[b] | T- stat |
|---|---|---|---|---|---|---|
| **ACBC** | **TMCPDAFL** | 0.531 | 0.308 | 0.223 | 0. 083 | 3.03*** |
| | **TMSPA** | 3092.88 | 1418.37 | 1674.51 | 541.86 | 4.80*** |
| | **AAOFHC** | 0.785 | 0.626 | 0.160 | 0.085 | 2.84** |

**ACBC =** adoption of cross breed cow**;** **AAOFHC** = availability of animal origin food for household consumption; **TMCPDAFL** = total milk consumed per day at farm level; **TMSPA** = total milk sold per annum in liter. *** and ** means significant at 1% and 5% probability levels, respectively; [b] The bootstrapped SE is obtained after 100 replications.

**Table 6:** Estimates of average treatment effect (ATT) on income indicators

| Intervention | Variables | Treated (Adopters) | Control (Non-adopters) | Difference | S.E.[b] | T- stat |
|---|---|---|---|---|---|---|
| **ACBC** | **TIMMP** | 24158.45 | 6501.47 | 17656.98 | 2512.73 | 8.29*** |
| | **ASCS** | 0.663 | 0.450 | 0.212 | 0. 103 | 3.57*** |
| | **AHLAA** | 0.362 | 0.182 | 0.180 | 0. 079 | 3.47*** |
| | **ABNFH** | 0.466 | 0.280 | 0.186 | 0. 112 | 3.42*** |

**ACBC =** adoption of cross breed cow**;** **TIMMP** = total income from milk and milk products; **ASCS** = allow to send children to school; **AHLAA** = allow to hire labor for agricultural activities; **ABNFH =** allow to built new or renovate the existing family house. *** means significant at 1% probability level; [b] The bootstrapped SE is obtained after 100 replications.

Then it was selected as a best fit matching estimator for this study.

## Testing of Covariates` Balance

The next task after choosing the best performing matching algorithm was to check the balancing of covariates by comparing the before and after matching algorithm significant differences using the selected matching algorithm. The balancing powers of the estimations were ascertained by considering different test methods such as the reduction in the mean standardized bias between the matched and unmatched households and equality of means using t-test. The mean standardized biases before and after matching are shown in the fifth column while the total bias reductions are reported in the sixth column of Table 4. In the present matching algorithm, the standardized bias difference in before matching is in the range of 3.2% and 70.6% in absolute value and t-values in the same table show that 75% of chosen variables exhibited statistically significant differences at before matching. After matching, the standardized bias differences for almost all covariates lied between 0.1% and 37.8% and all of the covariates were balanced. In all cases, it was evident that sample differences in the unmatched data significantly exceeded those in the samples of matched cases. Hence, the process of matching created a high degree of covariate balance between the treatment and control samples that were ready to be used in the estimation procedure.

## Estimating the average treatment effect of the treated (ATT) with the matched sample and calculating standard errors

Here, the dairy technology`s impact on the outcome variables (total income from milk and milk products; availability of animal origin food for household consumption; allow to send children to school; allow to hire labor for agricultural activities; allow to build new or renovate the existing family house; total milk consumed per day at farm level; total milk sold per annum in liter) were evaluated whether there was a significant impact on adopter households or not, with the pre-intervention differences controlled (Table 5 and 6).

Table 5 shows the estimates of average treatment effect (ATT) of dairy technology on production indicators such as total milk consumed per day at farm level (TMCPDAFL), total milk sold per annum in liter (TMSPA) and availability of animal origin food for household consumption (AAOFHC). As the result shows, the total milk consumed per day at farm level was 42% ((difference value/ treated value) * 100), which is significantly (p<0.01) higher in dairy technology adopter households than control groups (non-adopters). As it is also indicated in the same table, on average, the dairy technology adopter household sold 1674 liters more milk per annum than the non-adopters and this result is statistically significant at 1% level. Regarding to the availability of animal origin food for household consumption, it is 20% more practiced in adopters than non-adopters and it is statistically significant at 5% level.

As it is indicated in Table 6, total income from milk and milk products (TIMMP), allow sending children to school (ASCS), hire labor for agricultural activities (AHLAA) and allow to build new or renovate the existing family house (ABNFH). Regarding total income from milk and milk products, the result shows that on the average, treated households (adopters) got 73% more income from milk and milk products per annum than the controls (non-adopters) and this difference was statistically significant at 1% level. The average treatment effect of the dairy technology on sending children to school is also shown in the same table and it reveals that dairy technology adopter households got 32% more opportunity to send children to school than non-adopter households and the result was significant at 1% level. Adopter households had also 50% and 40% more chances than non-adopters on hiring labor for agricultural activities and build new or renovate the existing family house, respectively; differences statistically significant at 1 % level.

## DISCUSSION

Estimates of average treatment effect on treated of dairy technology results revealed that total milk consumed per day at farm level was 42% higher in dairy technology adopter households than control groups (non-adopters) and the dairy technology adopter household sold 1674 liters more milk per annum than the non-adopters. This is because of adopter smallholder farmers used improved breeds and improved techniques in feeding, breeding and animal health to increase milk productivity. This result in agreement with the result of (Mosnier and Wiek, 2010) stated that Technology plays a major role in dairy production because production can be done anywhere as long as traditional constraints are abated by improvements in technology.

Propensity score matching analysis also showed that adopter smallholder farmers could get 73% more income from milk production on average than the non-adopter smallholder farmers. This is may be due to there is a positive relationship exists between the productivity of a herd and the income received by the farmer per cow. If the milking herd was more productive, the more milk the farmers produced and the more income they received from selling it in the area where the milk market accessible. This result is in line with the finding of (Medola, 2007) which stated what farmers gain from new agricultural technology has a direct influence on the poor households by raising their income while indirectly raising employment and wage rates on landless laborers.

## CONCLUSIONS AND RECOMMENDATIONS

Adoption of dairy technology (crossbred cow) is associated with increased milk production and income which results in improving the smallholder livelihoods. This implies that introducing and disseminating appropriate dairy technologies to smallholder farmers with a continuous follow up could be a means through which their livelihoods can be improved and it enables to narrow the milk demand – supply gap in both rural, peri urban and urban consumers which has a good public health implication at the nation wise. Accordingly, the following recommendations were forwarded.

1. Introducing different dairy technologies should be supported with a continuous training or technical backup on how to manage and utilize the technology as well.
2. Even though cross breed cows give a better milk yield per day, still both breeds (local and cross breeds) provide less than their potential. Therefore, different actors should work collaboratively to increase the productivity and production of the dairy sector.
3. Having an experimental study for cost-benefit analysis of dairy technology (cross breed cows) adoption is very important.
4. A sustainable supply of cross breed heifers/cows with the reasonable cost and supported with continuous training or technical backup how to utilize them and manage farms is needed for smallholder farmers.

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