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Research Title:

Does dairy feed technology adoption in Ethiopia have an impact on milk production? Impact Estimation with Matched Difference-in-Differences Technique

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ABSTRACT:

In Ethiopia, the need to increase dairy productivity is a pressing necessity. To this end, the adoption of relevant technologies has been in place. However, the effect of the interventions was not yet sufficiently and rigorously identified. In this study, the impact of dairy feed technology on milk production in rural and small towns of Ethiopia is estimated. The study analyzed a socioeconomic panel data from 3,776 households. Combined Propensity Score Matching and Difference-in-Differences method using Inverse-Probability-Weighted Regression-Adjustment estimator was employed to estimate treatment effects. The finding shows that the average treatment effect is positive and significant ($p<0.05$) with a value of 74.43 liters per lactation period per household. Average treatment effect on the treated is 90.43 liters per lactation per household ($p<0.01$).

Dairy feed technology has a positive and significant effect on milk production in rural and small towns of Ethiopia. However, the overall level of household's milk production is even far below the national potential for some selected local and improved cattle breed's production. There are large numbers of households still dependent on traditional dairy feeds. These necessitate the need to the exertion of further effort to adopt dairy feed technologies at a household level.

KEYWORDS:

Impact Estimation; Matched Difference-in-Differences; Dairy Feed Technology; Milk Production; *teffects ipwra*; Ethiopia

JEL code: O- O2- O20

INTRODUCTION

Ethiopia is predominantly an agricultural economy and known for its huge number of cattle population. The agricultural sector accounts for about 46 percent of national gross domestic product (GDP), 90 percent of exports, and 80 percent of employment (AfDB, 2012). In Ethiopia, 90 percent of the poor rely for their livelihood on crop and livestock production (Yu *et al*., 2011). The contribution of the livestock sub sector is about 27% of the agricultural GDP. Dairy production is also known for its role as a source of income through the sale of raw milk and milk products. A dairy cow serves not only as wealth and insurance but also as a valuable source of household (HH)[1] nutrition. The latter is even more worth as far as children are concerned. This is because chronically undernourished children are economically less productive as adults (Hoddinott *et al*., 2014).

Despite a large number of cattle, the country remained a net importer of dairy products (Yilma *et al.,* 2011). This is attributed to the subsector's low productivity which is below the level of most developing countries (Melesse *et al*., 2013; MOFED and MoA, 2011; EEA, 2006). Studies indicate that production of milk per animal is extremely low and it is only 1.85 liters per cow per day in Ethiopia (Dehinenet *et al*., 2014; SNV, 2011; CSA, 2008). Reports further indicate that the average lactation milk production for the indigenous cows' ranges from 494–850 liters under optimum management (CSA, 2011). Also, consumption of milk and milk products is also below the standards of most developing countries. Felleke *et al.* (2010) indicated that the per capita milk consumption of Ethiopia is only 20kgs per annum. This is below the average for Sub-Saharan Africa (25kg) as well as below the average for neighbor Kenya (90kg). It is by far lower than the FAO/WHO recommended amount (200 liters per capita per annum). This necessitated

[1] HH - Household

the commitment by the government and other development partners to give due emphasis to increase production and productivity thereby increase utilization of dairy products.

In countries like Ethiopia where there is high population pressure and where both cultivable and grazing land is scarce, expanding cultivated land is not a recommended approach to increase agricultural production. As a result, future growth of agriculture must rely on improved technologies which help to increase agricultural production through its effect on agricultural productivity (World Bank, 2008).

Increasing dairy productivity is a very fundamental issue for improving livelihood and enhancing food security in Ethiopia. The low dairy productivity and hence low milk production in Ethiopia combined with the need to increase it through dairy feed technology (DFT)[2] necessitated the widespread adoption of proven dairy feed and management technologies both by the government and different development partners (Felleke *et al*., 2010). The technology dissemination approach is a package-driven extension through which different agricultural technologies were combined with credit facilities and better management practices (Yu *et al*., 2011).

Though the interventions resulted in the improvement of productivity and reproduction efficiency of dairy animals (Melesse *et al*., 2013), the impact of those efforts has not yet been well evaluated and documented.

In evaluating the impact of agricultural technologies in Ethiopia, there is relatively higher emphasis given by researchers towards crop production technologies in general and that of fertilizer, improved crop varieties and agronomic practices in particular(Zegeye *et al*., 2001; Doss, 2003; Matsumoto & Yamano, 2010; Mulugeta & Hundie, 2012). Other similar studies include studies which were focused on estimating the impact of Productive Safety Net Program

[2] DFT – Dairy Feed Technology

(PSNP) (Andersson *et al*., 2009; Gilligan *et al*., 2009; Alem & Broussard, 2013); evaluation of Ethiopia's food security program (Berhane *et al*., 2013); impact of roads and agricultural extension (Dercon *et al*., 2008); effect of social protection influence on livelihood diversification (Weldegebriel & Prowse, 2013); the impact of perception and other factors on the adoption of agricultural technologies (Negatua & Parikhb, 1999); agricultural extension and its impact on food crop diversity and the livelihood (Biratu, 2008). But, to the best of authors' knowledge, impact studies on livestock technologies are very much limited.

However, there are interventions and signals of the effect on dairy technologies in general and that of DFT's in particular. But, the impact of DFT's adoption is not well studied and documented. To the best of the authors' knowledge, empirical works concerning the impact of DFT on milk production are almost absent in the country. If there are some researches done, their geographical area, or study population as well as methodologies employed or outcome variable considered are different. Such studies include studies by Gunte, 2015; Dehinenet*et al*., 2014; Amlaku *et al* 2012 in Melesse*et al*., 2014; Melesse& Jemal, 2013; Goshu*et al*., 2013; Kluszczynska, 2012; Mekonnen *et al*, 2010. But these limited studies have not carried out Difference-in-Difference Method (DiD) combined with PSM, which is a method highly recommended to capture both observable and unobserved heterogeneity. Also, those studies tend toward estimating other outcome variables than milk productivity and production which is the concern in this study. The impact estimation in this study, unlike the above-mentioned studies, is also at national scale. These indicate that there is a huge research gap in the area towards which this research intends to contribute.

The objective of this study is to estimate the impact of DFT on household's cattle milk production in rural and small towns of Ethiopia. In countries like Ethiopia where poverty is pervasive and the capital shortage is severe, the wise use and allocation of resources are decisive. There is also a shift globally in measuring hierarchy of changes brought about by interventions. This condition compels one to have a clear understanding of the effects of interventions as well as knowledge on how and when to disperse the limited money and effort. This study will help a lot in providing credible estimates of the effects of the endeavors to make evidence-based policy and planning on the management of the subsector's technology selection and diffusion process. This is because it offers reliable information on the extent of contribution for planners, policy analysts, consultants, and others so that they can recognize the need to improve interventions at various stages of implementations as well as the type of the technology itself. The study will also contribute to the literature gap found in the not-well-studied lacuna of the subsector as well as on impact evaluation methodologies.

1. CONCEPTUAL FRAMEWORK

Any development intervention (program or project) has its own objective when designed and implemented. The focus of evaluation nowadays is on measuring such changes on results, both intended and unintended. This needs tracking the different chains of the changes after the intervention. Program or project monitoring and evaluation is made simple by the use of the logical framework. The frame begins with the supply of different resources (inputs) and subsequently end with different chains of subsequent objectives (Rogers, 2012).

Dairy technology as an intervention also needs a description of how its application logically could bring desired objectives. This is explained by the conceptual framework on Figure A. The adoption of different DFT by farmers in a given period of time should first be considered from the point of maximization of the expected utility (expected profit), which is subjected to different constraints. This depends on farmer’s distinct choice of feed technology from among different combinations of technologies. The technology combinations could be traditional or a set of components of the modern technology package (Feder *et al.*, 1982). Thus, adoption decision to dairy technology is subject to different factors surrounding the farmer's condition. Once a farmer decides to adopt or not, and also constrained or not to utilize the available DFT, he/she will be exposed to different inputs depending on his/her choice. Those farmers who didn't adopt the modern DFT will be continuing with the traditional feed technologies (input 1). But those farmers who choose to adopt the modern DFT will be exposed to both traditional (input 1) and modern feed technologies (input 2). The adopters will then select among the different modern DFT packages subject to their constraints. This will lead farmers to two pathways: the non-adopters' pathway having only traditional dairy technologies, and that of adopters' having feed adoption intensity. Once the farmers adopt any of the available feed technologies subject to their constraints, they will continue to be engaged in their respective activities, and they will have their own input-activities-output-outcome-goal-pathways (Figure. A).

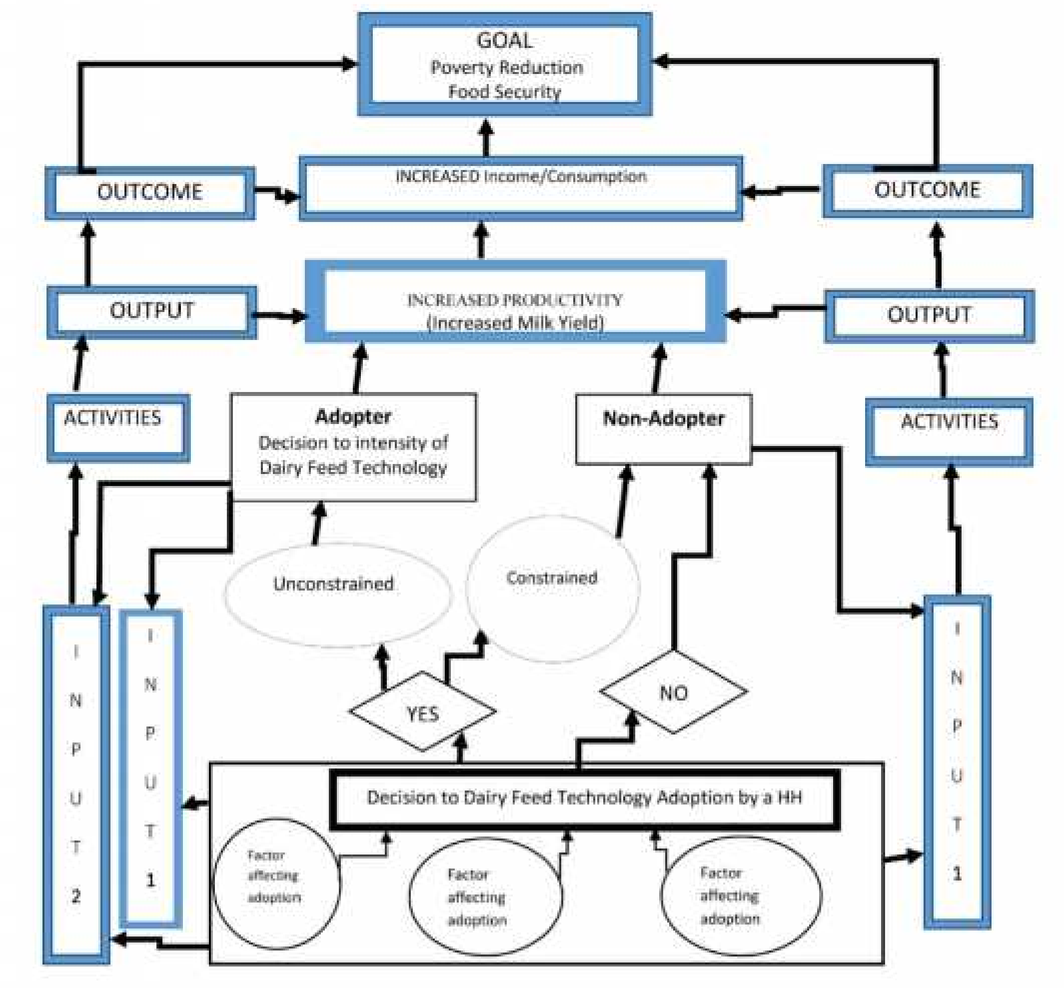

Figure A. Framework for dairy feed technology adoption and its effects (Source: Own construction)

Caption: Technology adoption is considered to occur in two-stage processes. Adopting farmer need to be willing to adopt. Once willing, he must pass the different constraints up in front of him. The choices available to him include not only the modern technology packages (input 2) but also the traditional choices (input 1). Non-adopters utilize input 1 only. But adopters make use of both input 1 and 2. The effect of technology adoption will be revealed along the results chain.

2. EXPERIMENTAL METHODS

3.1. The Study Area and Data

Ethiopia is in North East Africa with latitude and longitude of 8° 00 N and 38° 00 E. The country is one of the most populous nation in the continent next only to Nigeria. The total population and rural population projection of the country in 2017 are estimated to be more than 94 million and 75 million, respectively. The country is also known for its huge livestock population (49.3 million cattle) both in Africa and in the world (Yilma *et al.*, 2011).

This research relies on multi-topic panel data from the two recent waves from Ethiopia's Living Standards Measurement Study (LSMS), which were conducted by the Central Statistical Authority of Ethiopia (CSA) with technical support from the World Bank in the years 2011 and 2013. The samples are representative for the national, rural and small towns of Ethiopia. The data is also representative of the four regions (Oromiya, Amhara, SNNP, and Tigray) and also to the other regions taken together (Afar, Benishangul-Gumuz, Gambella, Dire Dawa, and Harari) (CSA & LSMS, 2013;2015). The data on the two waves focus on HHs and on their welfare characteristics and agricultural activities (CSA & LSMS, 2015).

The sample design employed by CSA while collecting the data sets was a stratified, two-stage probability sampling. The strata were the Regional States. Quotas were set for the number of enumeration areas (EAs) in each Region to ensure a minimum number of EAs. According to CSA (2014), an EA in the rural parts of the country is a locality that is in most cases less than and in some cases equal to a farmers' association in a geographical area and usually, it consists of 150 to 200 HHs.

The first stage of sampling was selecting the EAs (i.e. the primary sampling units) through simple random sampling technique. The second stage of sampling was the selection of a total of

12 HHs to be interviewed in each EA.The samples were represented from 290 rural and 43 small towns EAs. Since the successfully re-interviewed number of HHs is 3,776 from 333 enumeration areas, the panel analysis of the study employed only this sample (CSA & LSMS, 2015).

Since the unit of analysis for the study is a HH, the data were merged using the unique identifier, i.e., HH identification number (id). Different variables were also constructed based on their theoretical definitions. This include, for instance, construction of milk production per liter per lactation period, farm- and non-farm income to construct total HH income, use of elevation for defining traditional agro-ecological zones', use of fields and parcels to construct total household landholding, use of cattle in household for constructing Tropical Livestock Units, use of household size to construct Adult Equivalent size, etc. Data cleaning was also carried out.

Datasets from both waves are weighted. This was to represent the national-level population of rural and small-town households. A population weight was calculated for the households and this weight variable was included in all the datasets. When applied, this weight helped raise the sample HHs to national values for rural areas and small towns. The expansion factor was applied with respect to the recommendation given by CSA & LSMS (2015a). This is to produce an estimate for the population of individuals in a HH level. And hence, an approximate expansion factor used here is the sample weight times the HH size of each HH.

3.2. Program Intervention and Operational Definition of Variables

3.2.1. Nature of the intervention (Program Treatment)

Agricultural extension as well as different livestock programs and projects, including DFT, are carried out in the country both by the government and non-governmental development partners. They presented the different kinds of dairy feeds to farmers either in a single type or as a package. The farmer may then utilize by selecting any amount and type(s) from among the available technologies.

3.2.2. Operational definition of variables

Household (HH)

Unit of analysis in this study is a household. The CSA/LSMS document (CSA & World Bank, 2011:7)define a household as:

> *"…is either a person living alone or a group of people, either related or unrelated, who live together as a single unit in the sense that they have* ***common housekeeping arrangements*** *(that is, share or are supported by a common budget).*

Rural and Small Towns

The Central Statistical Authority of Ethiopia indicates that small towns are towns with the population of fewer than 10,000 people and with urban settings. The study considers those areas with the less population and sparse human settlement than small towns', as well as without urban settings as rural areas.

Dairy Feed Technology Adoption

Dairy feed technology package components', like that of any other agricultural technology packages, though important for better results if used together, they may not be used together(Feder *et al*., 1982). Hence, the farmer may adopt complete package or any of the accessible components due to various constraints imposed upon him. In developing countries like Ethiopia, a farmer also continues to adopt different DFT while still maintaining the traditional practices. Thus, feed technology adoption in this study is considered as percent utilized of one or any combination of those available DFT.

Feed Technology Non-Adopters

Allowing animals to graze green fodder in the pasture is traditional and low productive way of rearing livestock in Ethiopia. Hence, it is not considered as feed technology in this study. So, HHs using amount greater than or equal to 90% of feed materials from grazing on green fodder, or green fodder grazing and 10% crop residue are non-adopters. For impact evaluation, adopters are defined based on the 2013 survey data. The crop residue combination with such amount is necessary because those farmers in the mixed crop-livestock production system have more chance of feeding their cattle with crop residues at least in the main harvest season. Excluding this fact will not help to explore the reality on the ground. It will be impractical to avoid utilization of some amount of crop residue in the HHs with both livestock and crop farming. Hence, in this study, crop residue utilization less than or equal to 10% was not considered to be a technology adoption.

Feed Technology Adopters

Using different types of improved feed types like supplementary feeds and concentrates in one or other way is related to increased milk production and productivity. The reason is that milk production requires a lot of energy and other nutrients (Lukuyu *et al.*, 2007). Utilizing these feed types require improved methods of harvesting, handling and storing. And hence, HHs utilizing a combination of crop residue, hay, improved feed and/or agro-industrial by-products are considered to be feed technology adopters. A combination of any one of these feed types when utilized more than 10% are considered to be DFT. But, crop residue, if utilized alone, it should be utilized more than 10% to qualify as DFT.

Treatment and Outcome Variables for Impact Evaluation

Dairy feed technology adoption is a treatment (intervention) variable in this study. The outcome variable in this study is the amount of milk production. HH's total milk production per lactation period in days measured in a liter is used to see the impact of feed technology. This variable is constructed from the dataset by changing all other units like kilograms, grams, and other traditional units like cups and glasses into the common and standard measurement by using the international metric system. Average lactation period for each HH in months is found in the data set. The total HH milk production in liters (*TMilk*)is then calculated as follows:

TMilk=

[Milk yield per cow per day (liters)]*[average lactation period (days)]*[lactating cows in the household (number)]

Participants and Non-Participants

Participants are those HHs who actually get involved in adopting DFT. Both groups (treated and control) are not participants in time period one (2011). But, in time two (2013), there are both participant and non-participants.

Non-participants are those HHs who actually are not get involved in adopting DFT as per the requirement in this study. These groups are existing in both time-one and time-two.

Treatment Groups and Control Groups

Treatment groups are those participants who actually get involved in adopting the treatment. But those participating HHs in time two are also treatment groups in time one. So, treatment groups are available in both time periods.

Control groups (untreated groups) are those non-participant HHs which are identified by having propensity score closest to the participants. They then serve as a comparison group. By this, they help to estimate the counterfactual outcomes.

Propensity Score

The propensity score is the probability that each HHis participating in DFT adoption in the second period (i.e., 2013) given variables (X) of observed characteristics of the first period. It is a single number ranging from 0 to 1 and it outlines all of the observed characteristics.

Matching

Matching is the process of finding those HH which could be the closest artificial comparison group from a sample of non-DFT adopters (non-participants) to the sample of those HHs who actually adopted DFT (participants).

Based on the propensity score obtained from baseline characteristics, treated and untreated comparison groups will be matched with panel set using inverse-probability-weighted regression adjustment.

3.2.3. Variable Choice and Definition

The choice of variables was based on the findings from theoretical and empirical review of potential factors affecting DFT adoption. Variables which might be affected by DFT, those variables hypothesized to be associated with feed technology but not with milk production, are not kept in the model. Common variables like sex and contextual variables like Regions, rural, agro-ecology, etc. are included. Several trial and errors were performed among those selected variables to specify that propensity scores are balanced across adopters and non-adopters within blocks of the propensity score. The dependent variable, i.e., DFT adoption is specified with the assumption of two-stage adoption processes (see conceptual framework on Figure 1) with panel hurdle model. The different explanatory variables which were supposed to affect the adoption of DFT in one or two of the stages are described in Table A.

Table A. Summary of Variables Used (Source: Authors, Unpublished result)

Variable Name	Measurement of the Variables
Explanatory Variables	
Age of HH* Head	Age dummies: dAge1= $\begin{cases}1 \; ifageofHHheadis < 30 \\ \quad 0 \quad else\end{cases}$ dAge2= $\begin{cases}1 \; ifageofHHheadis \geq 30 \; and \; < 50 \\ \quad 0 \quad else\end{cases}$ dAge3)= $\begin{cases}1 \; ifageofHHheadis \geq 50 \\ \quad 0 \quad else\end{cases}$
Sex of HH head	Male_dummy= $\begin{cases}1 \; ifsexofHHheadismale \\ \quad 0 \quad iffemale\end{cases}$
Family size in terms of adult equivalent (AE_hh)	Converted from household size and age data into adult equivalent size
HH Landholding (Total)	Crop fields in hectare (constructed from meter square) and transformed into logarithm (log_landH)
HH distance to the nearest market	In kilometers (dist_market)
Total livestock holdings	Tropical Livestock Unit/ (TLU) Constructed and transformed into logarithm
Rural indicator	Dummy (rural_dummy): $=\begin{cases}1 \; ifaHHisresidinginruralareas \\ 0 \quad iftheHHisresidinginsmalltowns\end{cases}$
Access to post planting crop/agricultural extension	agri_extn_dmy $=\begin{cases}1 \; ifYestopostplantextensionparticipationbyHHhead \\ \quad 0 \quad ifNo\end{cases}$
Traditional agro-ecological zones	Dummy (dtAEZ) $=\begin{cases}1 \; ifhighlands(Dega,Wdega,Wurch,Kur) \\ 0 \quad ifLowlands(Bereha,Kolla)\end{cases}$

Shock (drought)	ddrought $=\begin{cases} 1 & if Yes(encountered drought as a severe challenge) \\ 0 & if No \end{cases}$
Agricultural Engagement	FarmT_dummy$=\begin{cases} 1 & if engaged in livestock only \\ 0 & if both in crop and livestock \end{cases}$
Dry season water accessibility by HH	Dwater_dumy= $\begin{cases} 1 & if access to dry season water is easy to the HH \\ 0 & if difficult \end{cases}$
Years of schooling of HH head	Years of schooling of the HH head from illiterate (cannot read and write up to Ph.D.) (Scholing_yrs**)**
HH access to credit	credit_dummy $\begin{cases} 1 & if yes to access to credit service by the HH \\ 0 & if No \end{cases}$
Gross annual HH income	log_tot_hh~2; transformed to logarithm; measured in Ethiopian Birr (constructed from farm and non-farm HH incomes)
Cost of livestock production	cost_prdn_ls costs associated with feed, vaccine and drug for livestock in ETB
Region dummies	Regional States of Ethiopia
dOromiya	$=\begin{cases} 1 & if Oromiya national region \\ 0 & else \end{cases}$
dAmhara	$=\begin{cases} 1 & if Amhara national region \\ 0 & else \end{cases}$
dSNNP	$=\begin{cases} 1 & if South NNP national region \\ 0 & else \end{cases}$
dTigray	$=\begin{cases} 1 & if Tigray national region \\ 0 & else \end{cases}$
dOthers	$=\begin{cases} 1 & if Afar, BGumuz, Gambela, Dire Dawa, Somali, Harari regions \\ 0 & else \end{cases}$

*HH for household

3.3. Model specification with Difference-in-Difference matching (DiD-cum-PSM)

There are different DFT interventions undertaken in Ethiopia. Those interventions were targeted HHs' based on the interests of the program designers' own criteria. In addition, the farmer also self-selects the program. Hence, there is expected selection bias. Randomization trials will not work because of the above realities on the ground. Propensity score matching (PSM) based on cross section data may also produce biased estimates because of the fact that the selection process had not been fully observed. When data before and after a project are available, panel data methods such as difference-in-differences (DiD)or fixed effects regressions are widely used to measure the impact of a project. When only two-period data are available, DiD method is employed (Wooldridge, 2012). But using DiD alone will limit the study to consider only observable differences. When DiD is combined with PSM, the shortcomings of both PSM and DiD methods will be improved (Khandker *et al.*, 2010; Cuong, 2015). Hence, in this study, a quasi-experimental method using combined DiD-PSM technique was employed.

3.3.1. Matching without baseline Panel Data

The ideal DiD estimator needs a comparison of participants and nonparticipants before and after the program intervention. This implies that baseline survey (initial situation) of both non-participants and (later) participants, as well as additional survey of both groups need to be conducted so that the difference is calculated between the observed mean outcomes for both groups before and after the intervention (Khandker *et al.*, 2010; Gertler *et al.*, 2011). But in practice, a baseline survey is not conducted. The problem is worse in developing countries. According to Bamberger (2010), some of the reasons for not conducting baseline studies include lack of awareness of the importance of baseline data, a lack of financial resources, and/or limited technical expertise.

In this study, too, there were no baseline data. However, the problem was overwhelmed by appropriate specification and procedure. The datasets are available for both t (2011) and $t+1$ (2013) but the program was already in place in t (2011). In such case where there is no strict before and after scenario, the DiD method can still be implemented with some alternative ways (Cuong 2010a; Doss, 2003; Feder *et al.*, 1982).

One alternative method to deal with theno-baseline condition is done by discarding all program participants in period t (initial period) from the data. This is applicable because the group of non-participants in both periods (t and $t+1$) were large enough. The usual PSM method to find the propensity scores, P(X), based on all observed covariates X that jointly affect participation and the outcome of interest from the baseline data, i.e., from those observable characteristics not affected by program participation. This was done with the help of *pscore* command. While doing this, the balancing property of the PSM was assured to be satisfied. This guarantees that the HHs with the same propensity scores have the same distributions of all covariates for all the blocks categorized. The common support area is also identified. This process results in matched sample composed of closest comparison group from a sample of nonparticipants to the sample of program participants. This helps to reflect any observable heterogeneity in the initial conditions between the two groups.

3.3.2. Matched Difference-in-Differences

The matched sample HHs in the initial data created were kept for the subsequent merge with the panel $t+1$ data. The DiD method was then employed by matching with data in $t+1$ (2013) treated units to untreated units, and compute the difference in time in terms of mean outcomes for the two groups. Taking the differences in outcomes over time helps difference out time-invariant unobserved heterogeneities and thus potential unobserved selection bias.

3.3.3. Weighted Least Square Regression Framework

With the above issues in mind and following Hirano, Imbens, and Ridder (2003) and Khandker *et al.* (2010), for outcome on treatment T and other observed covariates X unaffected by participation, weighted least squares (WLS) regression framework is specified by weighting the control observations in line with their propensity score. The procedure results in a fully efficient estimator (Khandker *et al*., 2010).

$$\triangle Y_{it} = \alpha + \beta T_i + \gamma \Delta X_{it} + \varepsilon_{it} \text{ , ………………. (1)}$$

Where, β= DiD estimate and,

$$T_i = \text{Treatment indicator} = \begin{cases} 1 & \textit{if treated} \quad (\textit{adopter}) \\ 0 & \textit{otherwise}(\textit{non adopter}) \end{cases}$$

The weighted least square regressions are estimated for the treated and control HHs that are part of the common support identified by the propensity score matching. If $\hat{P}(X)$ is the estimated propensity score of HHs, i.e. the probability of being assigned to either treatment (Adopter) or control (Non-adopter) group given the value of a set of observed covariates, then the weights in the above regression equation are equal to 1 for treated groups (adopters) and to $\hat{P}(X)/(1-\hat{P}(X))$ for comparison groups (non-adopters). For an estimate of the ATE for the population, the weights would be $1/\hat{P}(X)$ for the participants and $1/\left(1-\hat{P}(X)\right)$ for the control group. Hence, weights are a function of the estimated propensity scores. Those weights can create a balance in covariates across treated and control groups and hence allow for an unbiased regression-based estimator of the effect of program intervention. The advantage of using a regression framework is the possibility of controlling for covariates or firm fixed effects, if the covariates are time-invariant (Khandker *et al.,* 2010).

3.4. Impact Estimation with *teffects*

3.4.1. Definition of terms

Gertler *et al*. (2011) defines impact evaluation as follows:

> *"Impact evaluations are a particular type of evaluation that seeks to answer cause-and-effect questions. … looks for the changes in outcome that are directly attributable to the program"* (Gertler *et al.*, 2011:7).

From the definition above, it can be understood that the main focus for impact evaluation is causality and attribution. Other scholars also showed that it is causality which distinguishes impact evaluation from other kinds of evaluations (Khandker *et al*., 2010). Causality means that specific action (such as adoption of DFT) leads to a specific, measurable consequence (more milk yield for instance) (Stock & Watson, 2007). Attribution also implies the credit that will be given only to an intervention such as DFT.

The estimation on the treatment effects in this study is based on *teffects* of Stata14 (StataCorp, 2015). The *teffects* command was introduced by Stata13 and have many desirable properties for measuring treatment effects (UW, 2015).

It is difficult to estimate the ATE (Average Treatment Effects) of DFT adoption by simply subtracting the sample means for the treated and control HHs. This is due to the fact that there are many other factors (covariates) which are related to the counterfactual (potential) outcomes and related also to DFT itself. But, once the covariates were specified and the analysis was conditioned on these covariates, the remaining effects on DFT are not related to the counterfactual outcomes. In real world then, DFT status is not randomized. This means that milk production and DFT are not necessarily independent. But, *teffects* will solve these missing data issue by conditioning on those covariates to make DFT and milk production independent.

StataCorp (2015) defines the treatment effects that can be estimated from observational data using the *teffects* command as follows:

i. Average treatment effects (ATE_S) is the average effect of the treatment in the population.

$$ATE = E(y_1 - y_0) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (2)$$

ii. Average treatment effects on the treated (ATET) is the average treatment effect among those that receive the treatment (T):

$$ATET = E(y_1 - y_0 | T = 1) \ldots\ldots\ldots\ldots\ldots\ldots\ldots (3)$$

iii. Potential-outcome means (POMs): if the treatment level is defined to be, T, then POM for treatment level *T*is defined as the average potential outcome for that treatment level:

$$POM_T = E(y_T) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (4)$$

3.4.2. Inverse-probability-weighted regression adjustment /IPWRA/ estimator

The IPWRA estimator is a doubly robust estimator that combines the outcome modeling strategy of regression adjustment (RA) and the treatment modeling strategy of inverse-probability weighting (IPW) (StataCorp, 2015). The RA model uses linear regression models to predict the outcomes of each subject and the IPW model uses a logistic regression model to predict treatment status. The IPWRA estimator combines both models. The main advantage of IPWRA estimator is that, although it requires us to build two models, correct specification of either of the two models still allows accurate estimation. And after all, when the regression function is correctly specified, the weights do not affect the consistency of the estimator (StataCorp, 2015).

The code used for obtaining ATE, ATET and POMs in such cases of weighted least regression is given by (StataCorp, 2015):

$$teffects\ ipwra\ (\boldsymbol{Y}\ x_1 \ldots x_k, linear)(\boldsymbol{T}\ x_1 \ldots x_k, logit), atet\ vce\ (robust) \text{.......... (5)}$$

Where **Y** is total milk production (linear outcome variable); $x_1 \ldots x_k$ are covariates; linear implies the linear regression model used to predict the outcome variable; **T** implies DFT (dummy for treatment variable) and logit imply the logistic regression model used to predict treatment variable (logit is the default character; but, probit option can also be used with no difference in results- see appendix A1 and A2; G1 and G2); *atet* and *ate* are ATET and ATE options; vce (robust) is for robust standard error to prevent the problem of heteroscedasticity.

4. RESULTS

4.1. Descriptive statistics on sample

4.1.1. Description sample and outcome variable

Table B presents the sample used in evaluating the impact of DFT on milk production. There are no participants at time 1 (2011). Non-participants and treatment groups at time 1 were 3421 and 1516HHs, respectively. At time 2 (2013), the number of participant and non-participant HHs were 1686 and 1773HHs, respectively. The treatment groups at time 2 were 1686 HHs.

Table B. Frequency of sample households

Survey Year	Sample size (n)	Participants	Non-participants	Treatment Group	Control Group
2011	3421(49.72%)	0	3421	1516	1905
2013	3459(50.28%)	1686	1773	1686	1773
Total	6880	1686	5194	3202	3678

Source: Own presentation with CSA/LSMS panel data

The outcome variable, total HH milk production, is a continuous variable measured in liters. The distribution for milk production by HH was examined with *sktest* and found to be positively skewed and leptokurtic (p<0.01). The statistical description of the outcome variable (total milk production per lactation period in liters) between adopters and non-adopters is presented in Table C.

Table C. Total milk production in liters per lactation period between adopters and non-adopters

Participation dummy	Min	Mean	SD	Max
0 (Non-participants)	0	305.4434	930.2663	18240
1 (Participants)	0	325.1105	914.7753	23760
Total	0	311.0316	925.8266	23760

Source: Own presentation with CSA/LSMS panel data

Two-sample Wilcoxon rank-sum (Mann-Whitney) test (see Appendix B) shows that the total annual milk output by HHs is statistically significantly higher in the group of adopters than in the group of non-adopters ($p<0.01$). This indicates that there is correlation between DFT assignment and milk production output that is conditional on observed covariates. In such cases, the treatment assignment is not ignorable. This justifies the use of matching methods to correct sample selection bias.

4.1.2. Description of Results of Propensity Score Matching

The result of matching on observable initial conditions by regressing 2013 participation variable on 2011 explanatory variables is shown in Table D.

Table D. Baseline propensity scores matching sample

Survey Year	Sample size (n)	Participants	Non-participants	Treatment Group	Control Group
2011	3421	-	3421	1516	1905
Total	3421	-	3421	1516	1905

Source: Own presentation with CSA/LSMS panel data

The output on propensity score balance (Appendix C1) showed that the balancing property was satisfied and it gave us predicted propensity scores from the baseline data. By this, the observable heterogeneities in the baseline (2011) condition were controlled. Among adopters, the predicted propensity score ranges from .0395363 to .9514983, with a mean of .6296822. The predicted propensity score among non-adopters ranges from .030245 to .9159817, with a mean of .4754756. Thus, the extent to which distributions of propensity scores in feed technology adopters and non-adopters overlap is identified by the common support region of [.03953635, .9159817]. This is shown in Table E. The implication for this is that those HHs with estimated propensity scores less than .03953635 and greater than .9159817 are not included in the matching process.

Table E. Summary statistics of propensity scores for both participants and non-participants

Participation dummy	Frequency on support	Frequency Off support	Min	Mean	SD	P50	Max
Non-adopters	1888	4	.030245	.4754756	.2238512	.4788163	.9159817
Adopters	1529	0	.0395363	.6296822	.1983588	.6836424	.9514983
Total	3417	4	.030245	.559582	.2238687	.586938	.9514983

Source: Own presentation with CSA/LSMS panel data

The Ideal condition for the common support is that propensity score distributions between the treated and control groups would overlap entirely (Lanehart *et al.*, 2012). The result from the propensity score distribution (Appendix C2), histograms of estimated propensity score (Appendix C3), as well as from the kernel density estimation (Figure B) for both treated and control groups show that there is a very wide area in which the propensity scores of the two groups (treated and control) are alike. This implies that the two groups could match very well.

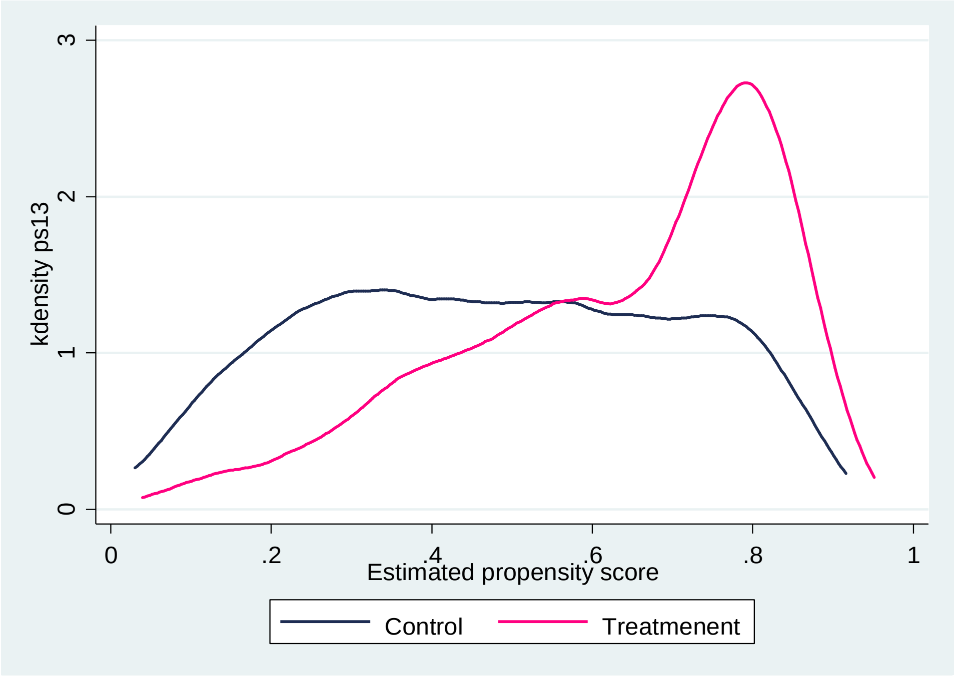

Figure B. Kernel density of propensity scores distribution. Source: Own presentation with CSA/LSMS panel data.

Note: Print requires color.

From the control group, 55.19% (1888/3421) HHs and from the treated group, 44.69% (1529/3421) HHs were on the common support. Only 0.0012% (4/3421) HHs in the control groups were off the common support. This indicates that we have sufficient observations from both groups.

The observable characteristics of technology adopted and non-adopted groups should be approximately equal. This was checked successfully with both covariate plot for each variable and with the use of overidentification test. The balance of the covariates can be seen visually from figure C1 and C2 taking HH land holding and access to post plant agricultural extension service as an example.

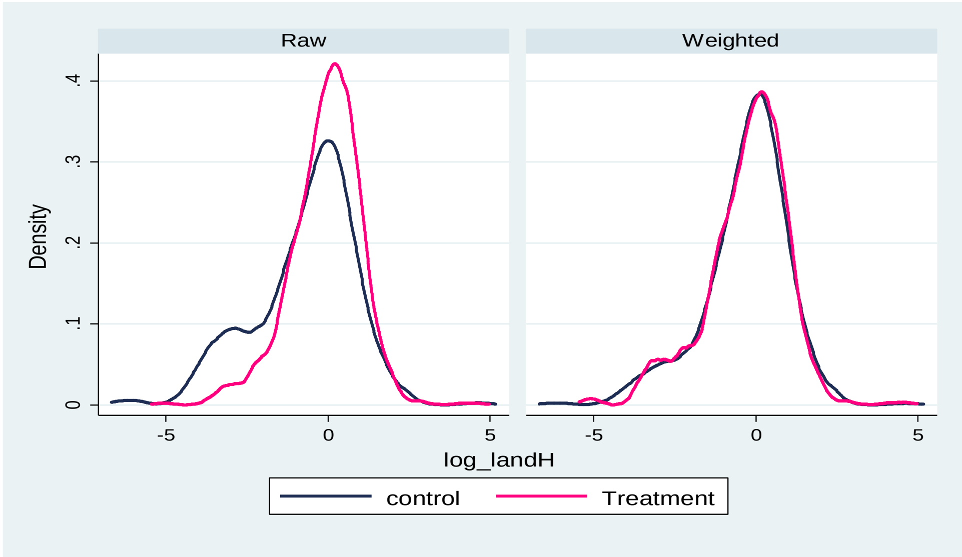

Figure C1

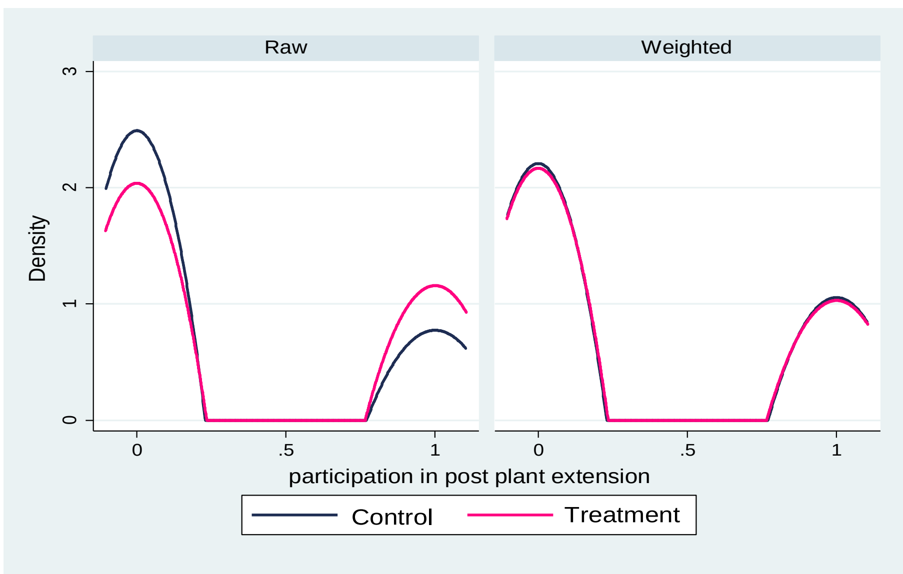

Figure C2

Figure C1 and C2 (above). Covariate balance plot (Household Landholding and participation in agricultural extension). Source: Own presentation with CSA/LSMS panel data.

Note: Print requires color.

Caption: Balanced data between the covariates of the two groups can be achieved by reweighting the observational data (like household's landholding and participation in post plant agricultural extension). This can be visually detected with balance plot in the figure. The more the weighted samples are indistinguishable, the more the estimated propensity score balance the covariate. The result here also indicates that the weighted distributions (densities) of land holdings between the two groups (Control and Treatment) are approximately equal. In such case, we successfully mimic randomization.

Note: Print requires color.

4.1.3. Description of results of difference-in-difference matching

The matching sample obtained from wave two data based on the propensity scores of baseline covariates (wave one data) is presented in Table F.

Table F. Difference-in-difference matching sample

Survey Year	Sample size (n)	Participants	Non-participants	Treatment Group	Control Group
2011	2220(52.00%)	-	2220	1197	1023
2013	2049(48.00%)	1213	836	1213	836
Total	4269	1213	3056	2410	1859

Source: CSA/LSMS panel data with own calculation

The matching sample shows that there were no participants in time one, and in time two, there were a total of 1213 HHs participating in program intervention, i.e., DFT. From the total sample obtained after difference-in-difference matching (n=4269), 52.00% are from t (2011) and 48.00% are from $t+1$ (2013). The total percent for treated group and control group is 56.45% and 43.54%, respectively.

4.2. Results on Treatment Effects

4.2.1. Results on Average Treatment Effects

The output on Average Treatment Effect (ATE) shows that the ATE was positive and statistically significant ($p<0.05$) (Table G). The finding indicates that DFT adoption causes dairy milk production of the HH to be increased by an average of 74.43 liters per lactation period per

HH from the average of 227.29 liters per lactation for those HHs who did not adopt DFT (see the Stata output in Appendix A1).

Table G. Treatment effect results for ATE and ATET

Total household milk production in liters per lactation period	Coef.	Robust Std. Err	Z	p>|z|	[95% Conf. Interval]	
Average Treatment Effect (ATE)	74.425	28.737	2.59	0.010	18.10195	130.7484
Potential-Outcome Mean (POmean)	227.288	19.716	11.5	0.000	188.6458	265.9295
Average Treatment Effect on the Treated (ATET)	90.432	34.72	2.60	0.009	22.3739	158.4904
Potential-Outcome Mean (POmean)	235.213	23.663	9.94	0.000	188.8354	281.591
ATE in percentage	.327449	.146829	2.23	0.026	.0396699	.6152286
ATET in percentage	.384469	.175016	2.20	0.028	.0414435	.7274944

Source: Own presentation with CSA/LSMS panel data

4.2.2. Results on Average Treatment Effects on the Treated

The result of Average Treatment Effect on the Treated (ATET), i.e., on those HHs who did, in fact, adopt the DFT, show that the ATET was positive and statistically significant ($p<0.01$) (Table G) (see the Stata output in Appendix A3). The finding indicates that among DFT adopting HHs, DFT causes milk production to be increased by an average of 90.43liters per lactation from the average of 235.21 liters per lactation that would have occurred if these HHs had not adopted feed technology.

4.2.3. Treatment Effects in percentage

Average Treatment Effect as a percentage of the mean milk production that would occur if no HHs adopt is employed for the purpose of easy scaling and interpretation of the result. The output using [coeflegend] option and *nlcom* command in *Stata* showed that DFT adoption increases the per lactation milk production of a HH on average by a statistically significant 32.7 percent ($p<0.05$). The average effect among the HHs who actually adopted DFT was also statistically significant 38.4 percent ($p<0.05$) (Table G) (see the Stata outputs in Appendix A2 and A4).

4.6 Post-estimation checks for assumptions

4.6.1 Post-estimation check for Overlap Assumption

One of the assumptions required in estimating treatment effects is the overlap assumption. The overlap here means that adopters with similar non-adopters can actually be matched. Thus, it is checked to see whether violated or not by drawing the overlap of the density of predicted probabilities between treated and control groups after estimating the ATE/ATET of DFT on milk production. When this assumption is not violated, the unobserved outcomes for the HHs can be predicted and accounted for. The estimated probability of a non-DFT-adopting HH is a non-adopter and the estimated density of the predicted probabilities that DFT-adopting HH is a non-adopter is presented in figure D.

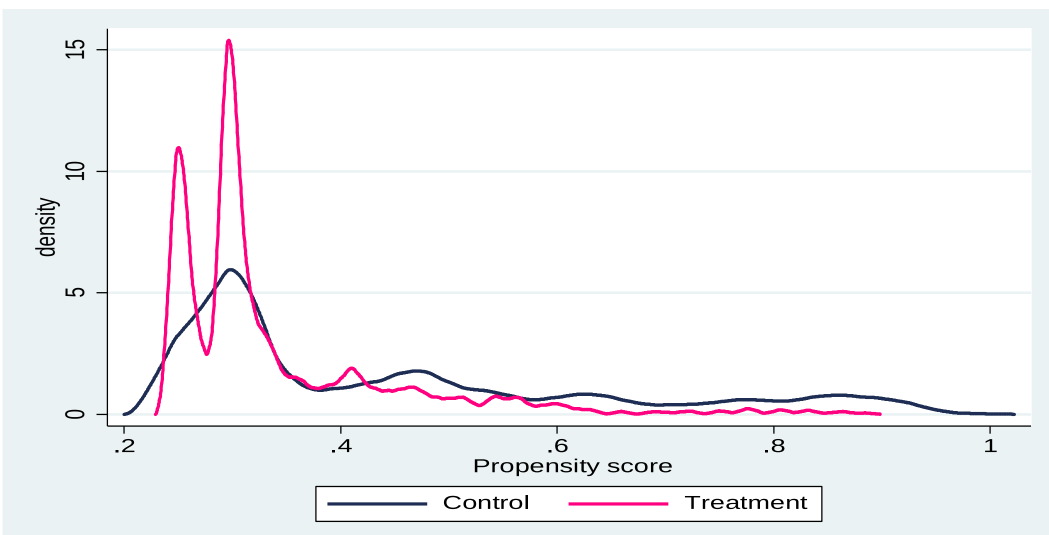

Figure D. Post-estimation test showing no evidence for violation of overlap assumption

Source: Own presentation with CSA/LSMS panel data

Caption: The correct estimation of counterfactual milk yield needs matching technology adopted households with those of similar non-adopters. This is possible only if there is no evidence for rejecting overlap assumption, or if the assumption holds true. The test result here indicates that each household have a positive probability of adopting the dairy feed technology. This means that we can accurately estimate the impact of DFT.

Note: Print requires color.

It can be visually detected from the overlap graph that the estimated density has no mass around 0 and 1. Rather, the estimated densities have most of their respective masses in the regions on which they overlap each other. This means that there is a likelihood of getting observations in both the control and the treatment groups at each combination of covariate values. Thus, there is no support that the overlap assumption is violated. This ensures that the predicted inverse-probability weights do not get too large and this, in turn, means that the IPWRA estimators have the double-robust property for the functional form combinations used. Hence, the effects of DFT on milk production can be estimated reliably.

4.6.2. Post-estimation check for Conditional Independence Assumption

In this study, assignment of households to the DFT adoption is assumed to be independent of the covariates. This can be checked by verifying whether the distribution of the covariates is balanced over treatment levels or not. The weighting in observational covariates was checked both by exploratory methods (Figure C1 and C2) and by formal test. Several trial and errors in specifying the model were made to achieve a superior balance. Overidentification test result applied indicted that we do not reject the null hypothesis that the specified treatment model balances the covariates (Appendix D). Hence, the model is well specified and the treatment estimates are credible.

4.6.3. Placebo Regression for Robustness Check

The panel data in this study consists of only two periods (2011 and 2013). Unbiasedness, in this case, can be checked by placebo regression (Gertler et al., 2011). Here, the outcome variable, i.e., milk production, is replaced by another fake outcome, i.e., outcome not affected by DFT. Other researchers who used placebo regression to test unobserved bias in impact evaluation include Abebaw and Haile (2013in Elias *et al.*, 2013) and Cunguara and Moder (2011 in Elias *et al.*, 2013).

In our study, the placebo regression was employed using adult equivalent size as (a fake) outcome variable (Table H) (see Stata output in Appendix E1andE2). The treatment variable was also included in the model.

Table H**.** Placebo regression using Adult Equivalent size

Adult Equivalent size (AE_hh)	Coef.	Robust Std. Err	Z	p>|z|	[95% Conf. Interval]	
Average Treatment Effect (ATE)	-0.0569	0.063	-0.9	0.368	-0.18088	0.670505
Potential-Outcome mean (POmean)	3.6379	0.054	67.7	0.000	3.53257	3.743216
Adult Equivalent size (AE_hh)						
Average Treatment Effect on the Treated (ATET)	-0.0373	0.0700	-0.53	0.594	-0.174623	0.100026
Potential-Outcome mean (POmean)	3.7289	0.06505	57.32	0.000	3.6014	3.8564

Source: Own presentation with CSA/LSMS panel data

The outcome variables are already known not to be caused by DFT. The regression on the above placebo outcome was conducted separately to check for both ATE and ATET. The findings for both ATE and ATET indicate that DFT does not have statistically significant causality on Adult Equivalent. This suggests that there are no significant omitted variables and unobserved characteristics are not influencing program participation that affects the impact estimates obtained. Therefore, the unconfoundedness assumption (conditional independence assumption) can be maintained. Hence, the causal interpretation of the results is plausible.

Also, though it cannot be proved, the validity of the assumption of equal trends can be judged with the help of the fake outcomes (Gertler *et al.,* 2011). Thus, the results on the fake outcomes above (Table H) indicate that the comparison groups for DFT adopting groups are not flawed. This means that the counterfactual estimates obtained were valid. Consequently, there is no evidence that, in the absence of the DFT intervention, the HH's milk production in the DFT adopting groups would not have moved in tandem with the milk production of that of the non-adopting comparison group's. This means that the estimated treatment effects are not biased and are valid.

5. DISCUSSION

Due to the difference either in methodology, treatment type or outcome interest, the impact evaluation findings on the specific issue to compare with are lacking in the Ethiopian context. But, somehow related work is the one done by Dehinenet*et al.* (2014c) on the impact of dairy technology adoption on livelihoods by using propensity score matching from cross-sectional data. Conducting this study in selected regions of Ethiopia, they found an ATET estimate 42% higher total milk consumption per day at farm level by dairy technology adopter HHs than non-adopters. In their findings, the dairy technology adopter HHs sold 1674 liters more milk per annum than the non-adopters. Not only their outcome variable is different from our study, but also their study was conducted on purposively selected high dairy potential areas and using only improved blood cattle. They associated the technologies with improved breeds and improved techniques in feeding, breeding, and animal health to increase milk productivity. But the positive effect of dairy technology is visible.

The study sample and, of course, the reality in Ethiopia (Felleke *et al.,* 2010) is that local zebu cattle by far outweigh the total number of cattle population. In this study, for instance, 98.75% of the total cattle population is local breeds. Ahmed *et al.* (2004) and Yilma *et al.* (2011) indicated that the milk production potential of the zebu breed in the highlands mixed crop-livestock system of Ethiopia is 400-500 kilograms of milk per lactation per cow. They also showed that the milk production capacity of local cattle of Boran, Horro, Barca, Arsi, and Fogera is 494 to 809 kg per lactation. The summary statistics in this study shows that the range of annual milk production in per lactation per HH is between 305 and 325 liters (313.59- 334.16 Kg)for non-adopters and adopters, respectively. Ahmed *et al.* (2004) indicated that the improved animals have the potential to produce 1,120-2,500 liters over 279-day lactation. This means that the milk production performance for the study population in this research is not only lower than the national average for local breeds but also it is far from the average potential for high-grade animals.

6. CONCLUSION AND RECOMMENDATIONS

The DFT adoption is found to have a significant effect on HH's milk production in rural and small towns of Ethiopia. It can be seen from the findings that those HHs in the rural and small towns' who adopted DFT are benefiting significantly more. This suggests that investing in smallholder dairy technologies pays off.

However, though DFT's adoption has a significant effect on milk production in rural and small towns of Ethiopia, the overall level of HH milk production level is even far below the national potential for some selected local as well as improved cattle breed's. This necessitates the need to the exertion of further effort to adopt DFT. Hence, the food security improvement and poverty reduction strategies of the country should not only focus on smallholder production but essentially need to be directed in a way to gain more from dairy farming. For this end, special emphasis should be taken to change the dairy production system into technology tapping venture. The number of HHs engaged on traditional farming (grazing on poor pasture for most of their times), needs to be substantially decreased. As the country's population is expanding from time to time, and as the per capita farmland is getting smaller and smaller, there is a need to simultaneously shift the farming system into labor-intensive-technology-based agriculture.

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