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Impact of Technology Adoption through Dissemination Innovation Platforms (IP) on Yield, Food Security and Poverty: Evidence from Major Wheat Producing Regions of Ethiopia

Tadele Mamo[1], Wudineh Getahun[1], Ali Chebil[2], Tolessa Debele[1] and Solomon Assefa[2]

Abstract

Despite the high wheat production potential of Ethiopia, domestic production has been unable to match domestic demand, forcing the country to be a net wheat importer. Several development activities have aimed at increasing improved technological adoption to boost wheat yield. These have used linear and top-down approaches to disseminate different technologies. Recently, a new approach known as a technology dissemination innovation platform (IP) has been tried in four of the major wheat producing regions by the Support to Agricultural Research for Development of Strategic Crops (SARD-SC) wheat project. Despite this, there has no empirical investigation of this approach. This paper details the result of investigating the impact of wheat technology adoption through a technology dissemination IP approach. It uses two period survey data collected from 506 sample households in 2012 and 2016. Household Food Insecurity Access Scale (HFIAS) measures were used to investigate the impact of the intervention on food security and a simple poverty scorecard approach to assess the impact on poverty. Both propensity score matching and difference-in-difference econometric models were utilized to investigate the impact on wheat yields. The results reveal that the intervention brought about a significant and positive impact on food security, poverty and wheat yield. Adapting an innovation platform approach would, therefore, have a positive impact on yield increment, food security and poverty in implementing projects that have

[1] Ethiopian Institute of Agricultural Research (EIAR)
[2] International Center for Agricultural Research in the Dry Areas (ICARDA)
Email addresses of authors are: mtadeleb@gmail.com; feked1983@gmail.com
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national importance. In addition, it is clear the current widely used, linear, top-down extension approach should be replaced by an approach that follows a technology innovation platform and which would provide a positive impact in these areas.

Keywords: propensity score matching, impact, wheat, technology dissemination innovation platform, Ethiopia
JEL Codes: D02, D13, Q12

1. Introduction

Wheat is used both as a staple food crop and an industrial crop in Ethiopia, an important cereal crop that is widely produced and consumed. During the 2015/16 meher cropping season, 1,664,564.62 hectares of land were allocated to wheat, producing 4,219,257 tons, implying a yield of 2.535 tons/ha (CSA, 2016). Both bread and durum wheat are grown in Ethiopia (Bekele et al, 2014). The consumption of wheat is gradually increasing especially in urban areas due to a growing population and changes in life style. However, despite the high potential for wheat production, domestic production falls short of domestic demand forcing the country to be a net importer of wheat grain. Only 70% of national demand is met from domestic production, the remaining 30% through import (Bekele e al, 2014). One possible reason for the gap between domestic wheat production and national demand can be attributed to the low productivity of wheat farming. The national average yield of 2.5 tons (CSA, 2016) compares to research station yields of 5.6 tons or farm yields of 4.4 tons per hectare (MoA, 2017). Low productivity can be attributed to the limited use of technologies and agro-ecological factors such as rain, temperature and diseases outbreak (Chilot et al., 2015; Araya et al., 2015).

To enhance wheat productivity and improve self-sufficiency in wheat, the wheat research program conducted by federal and regional research centers and assisted by different international agricultural researches, including the Center for Wheat and Maize Improvement (CIMMYT) and the International Center for Agricultural Research in Dry Areas (ICARDA), has been playing an important role. As a result, a lot of improved wheat varieties have been released and are under production. Adoption of improved wheat technologies is fundamental for increased productivity and farmers' livelihoods. However, for wheat technology to be effectively used, an effective dissemination strategy is necessary. This is usually done through the national extension program and mainly by the Ministry of Agriculture; some other projects and programs focusing on the wheat sector have also been able to assist the dissemination process.

However, the conventional Agricultural Research for Development (AR4D) processes in Ethiopia are based on linear and top-down approaches involving research, extension and farmers as the main actors, with research developing new technologies and disseminating these to farmers through the extension program. These approaches have been criticized for being supply-driven and having limited impact on the development, dissemination and adoption of agricultural technologies. Current trends show a shift from the conventional AR4D to the system of 'Integrated Agricultural Research for Development' (IAR4D) involving an Innovation Platform (IP) approach (Adekunle et al., 2013) with the goals of bringing various actors together to build networks and reach more farmers by stimulating an effective innovation system. The IP is inclusive and follows a participatory process among various stakeholders which helps to develop and make wheat technology packages available and support their wider adoption (Homann-Kee et al. 2015).

The Support to Agricultural Research for Development of Strategic Crops (SARD-SC) wheat project has been implemented since 2013 via an innovation platform (IP) approach, aiming at enhancing wheat productivity and provide income for increased food security and poverty alleviation. The project, financed by the African Development Bank (AfDB), focused on wheat technology generation, dissemination and adoption by creating a conducive environment for stakeholders to come together and strengthen farmers to maintain wheat production in selected high potential and low productivity IP sites. Technology dissemination using the IP approach has been practiced in six districts in four major wheat producing regions (Oromia, Amhara, SNNPs and Tigray). Wheat producers were supported in this intervention through revolving seed supplies along with pertinent training, providing participation in demonstration and popularization of best-bet wheat technologies, enhancing the dissemination process by providing training and organizing field days, and strengthening farmer-to-farmer technology diffusion. A total of 7906 farmers benefited from the intervention through training and obtaining improved seed in all four regions. The project targeted improved technology adoption to provide a positive change in wheat yield, food security and poverty reduction. Evaluating the impact of this wheat technology adoption through the IP approach before implementing similar technologies in other areas is important to ensure one can learn from the limitations and encourage positive outcomes. This research was designed to analyze this impact on beneficiaries in terms of wheat yield, food security and poverty.

There have been previous empirical studies on adoption and impact of agricultural technologies in general and on wheat in particular in Ethiopia and in the rest of the world (Awotide et al, 2012; Berihun et al, 2014; Bekele et al, 2000; Bekele et al, 2014; Morris et al, 1999; Tesfaye et al, 2016; Tsegaye and Bekele, 2012). Most of the previous studies have focused either on specific locations only or on single outcome variables due to the effect of technology adoption. This paper adds value to the existing literature in covering the impact of an intervention on several outcome variables at the intervention sites, namely wheat yield, food security and poverty reduction. This will allow other similar interventions to learn from the impact of wheat technology adoption through dissemination IP approach on wheat farmers yield, food security and poverty in major wheat producing areas of Ethiopia.

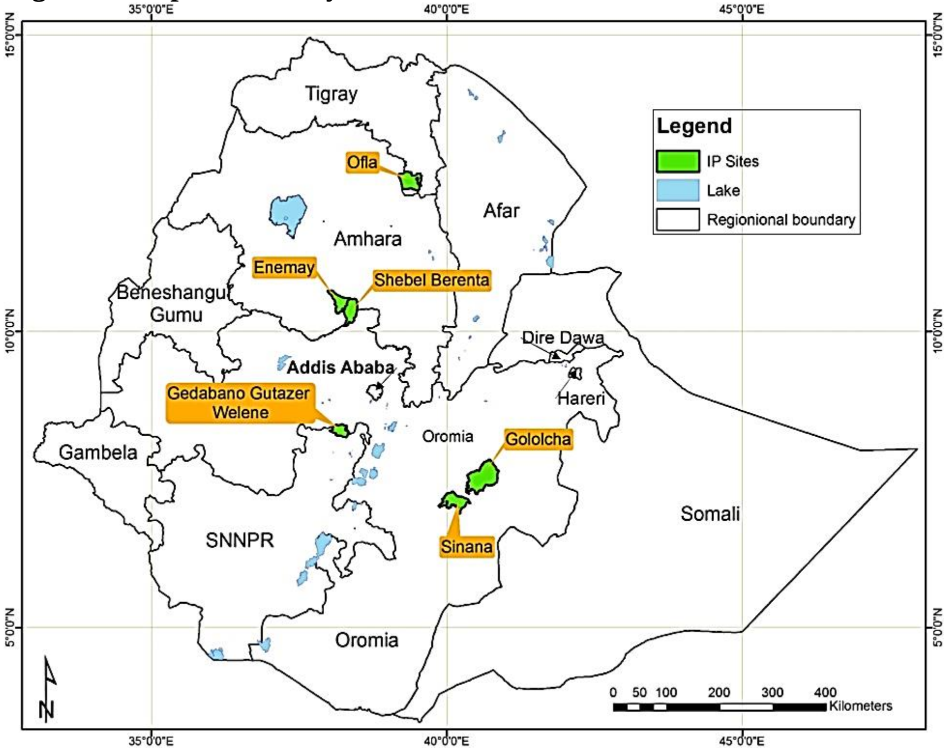
2. Methodology and the Study Approaches

2.1 The Study Area

The study of SARD-SC IP sites was conducted in six districts selected from the four major wheat producing regions of Ethiopia, namely Oromia, Amhara, SNNP and Tigray. These account for 99% of national wheat production, with production shares of 58%, 29%, 9% and 4%, respectively (CSA, 2016). Two districts from East Gojjam zone (Enemay and Shebel Berenta) of Amhara region, and Bale zone (Sinana and Gololcha) of Oromia region, and one district from the South Tigray zone (Ofla) of Tigray region and the Gurage zone (Gedebano Gutazer Welene district) of SNNP region, were selected. These districts were selected by the regions themselves for the SARD-SC wheat project IP intervention and they had not received enough attention and support from other development projects to enhance wheat production and productivity.

Figure 1 provides a map of the study areas within Ethiopia.

Figure 1: Map of the study districts, 2016



2.2 Data Collection Procedures

The SARD-SC wheat intervention activities took place in 18 kebeles and six selected districts (Ofla, Enemay and Shebele-Berenta, Sinana and Gololcha, and Gedebano Gutazer Welene) from four regions. The study utilized mainly primary data sources collected in two stages, a baseline survey conducted in 2012 and an end-line survey conducted during 2016. The primary data were collected from a total of 506 sample households (214 beneficiaries and 292 non-beneficiaries) drawn randomly from the list of wheat producer households from whom the baseline information was collected during 2012. With the same (506) households providing data for the end-line survey (2016) we covered two time periods for a total of 1012 observations. Table 1 presents the distribution of the sample households.

Table 1: Distribution of the sample households by IP site

Region	Zone	District	Non-beneficiary	Beneficiary	Total
Amhara	East Gojjam	Enemay	54	42	96
		Shebel-Berenta	42	47	89
Oromia	Bale	Sinana	67	29	96
		Gololcha	46	34	80
SNNP	Gurage	GGW	31	23	54
Tigray	South Tigray	Ofla	52	39	91
Total			**292**	**214**	**506**

GGW=Gedebano Gutazer Welene, SNNP=South Nations Nationalities and People
Note: A 506 sample in 2012 and the same 506 sample in 2016 provided a total of 1012 observations.

The primary data included detailed information regarding the socioeconomic characteristics of farm households, farm practices, access to agricultural services and qualitative food security and poverty related issues. In addition, a desk review was conducted to understand and conceptualize the impact assessment using different published and unpublished sources, and electronic and print media.

2.3 Method of Data Analysis

The data collected was analyzed and synthesized using different statistical and econometric tools. Descriptive statistics, means, chi-square test, t-test, were utilized to analyze the data and summarize information. Two econometric models, Propensity Score Matching (PSM) and Difference in Difference (DID), were employed to evaluate the impact of intervention on wheat yields. Using the two models in combination is more convincing and gives better confidence of impact evaluation (Gertler et al., 2016).

2.3.1 Analysis of the impact of intervention on food security

Household food security status can be assessed using quantitative approaches by calculating daily calorie intake or a qualitative approach through household food insecurity access scale (HFIAS) measurement indicators following Coates et al (2007).The HFIAS approach has the advantage of categorizing households into four categories: food secured, mildly food insecure, moderately food insecure and severely food insecure, rather than the usual ways of categorizing households into two: food secured, for those above the minimum threshold of calorie intake (2200 kilo calorie/day/adult), and all others food insecure. We used the HFIAS for this study. Coates et al (2007) suggests a questionnaire consisting of nine occurrence questions that represent a generally increasing level of severity of food insecurity (access), each having nine “frequency-of-occurrence” follow up questions to determine how often the condition occurred over the last four weeks. This category is based on the responses of the respondents to these nine occurrences and frequency of occurrence questions (Coates et al., 2007).

2.3.2 Analysis of the impact of intervention on poverty reduction

Rural household progress out of poverty can be evaluated using the simple poverty scorecard (Schreiner and Chen, 2009). The authors used the simple poverty scorecard of 11 low-cost indicators from Ethiopia’s 2004/5 Household Income, Consumption and Expenditure Survey and the 2004 Welfare Monitoring Survey to estimate the likelihood that a household had expenditure below a given poverty line ($1.25/capita/day for instance). Recently, there has been a new version of the simple poverty scorecard, reducing the indicators from 11 to eight (Schreiner, 2016). However, since the data for this research was collected in 2012 and 2016, it proved difficult to adopt this new version of the simple poverty scorecard; hence the older version has been utilized to evaluate the impact of the intervention of the wheat project on poverty reduction, using the two time periods (2012 before the project) and 2016 (the final year of the project). Measurement of the PPI for rural household and the indicators is annexed in the appendices.

2.3.3 Econometric models

For non-experimental design treatment and control groups, the two appropriate and most commonly used impact assessment econometric models are Propensity Score Matching (PSM) and difference-in-difference (DID) (Gertler et al., 2016). However, both have their own limitations and strengths. The PSM method is better as it matches and assigns the score of the matching to each observation based on the observed covariates. It is also to be preferred when there is no baseline data, but it needs a large sample size and cannot take care of unobserved factors that affect outcomes of interest which lead to selection bias. On the other hand, the DID method is used when both baseline and end-line data are available and it can handle small sample sizes. One of the serious assumptions necessary for the DID method to be valid is the parallel trend assumption that needs no difference in trends for both the treatment and control groups. Owing to the inherent limitations of either, combining the two methods is to be preferred to produce a confident report of the impact of the intervention (Gertler et al., 2016). In this study, we used both PSM and DID, using both whole and matched samples.

Propensity score estimation procedure to estimate impact on wheat yield

As revealed in Rosenbaum and Rubin (1983), matching can be performed conditioning only on P(X) rather than on X, where P(X) = Prob (D=1|X) is the probability of participating in the program conditional on X. They state that if outcomes without the intervention are independent of participation given X, then they are also independent of participation given P(X), reducing a multidimensional matching problem to a single dimensional problem. The implementation of the matching method is based on choosing a set of variables X (covariates) that reasonably satisfy this condition (Caliendo and Kopeinig, 2005). To guide this choice, economic theories, information from previous researches and about institutional settings are important to select appropriate covariates (Sianesi, 2004; Smith and Todd, 2005). The logit model can be used to assess factors influencing participation in the project. In estimating the logit model, the dependent variable is participation which takes a value of 1 if the household participated in a program and 0 otherwise (Gujarati (2004).

According to matching theory (Rosenbaum and Robin, 1983; Bryson et al., 2002; Jalan and Ravallion, 2003), the propensity score generated through the logit model should include predictor variables that influence the selection procedure or participation in the program and the outcome of interest. Based on the findings of previous empirical studies on impact assessments, relevant pre-intervention covariates (explanatory variables) were identified and included in the logit model for this study. To minimize the problem of unobservable characteristics in evaluation of the impact of the project, we included as many explanatory variables as possible in this study. The effect of household’s participation in the SARD-SC wheat project on a given outcome (Y) is specified as:

$$\boldsymbol{\tau_i = D_i(D_i = 1) - Y_i(D_i = 0)} \quad \textbf{(1)}$$

Where τi is the treatment effect (effect due to participation in SARD-SC wheat project), Yi is the outcome on household i, Di is whether household i has got the treatment or not (i.e., whether a household participated in the project or not).However, since Yi (Di =1) and Yi (Di =0) cannot be observed for the same household simultaneously, estimating individual treatment effect τi is impossible and one has to shift to estimating average treatment effects for the population rather than individuals. The most commonly used average treatment effect estimation is the 'average treatment effect on the treated' (τ ATT) which is specified as:

$$\boldsymbol{\tau_{ATT} = E(\tau|D = 1) = E[Y(1)|D = 1] - E[Y(0)|D = 1]} \quad \textbf{(2)}$$

Since the counterfactual mean for those being treated, E[Y (0) |D =1] is not observed, there is a need to choose a proper substitute for it to estimate average treatment effect on the treated (ATT). It might be thought that using the mean outcome of the untreated individuals, E[Y (0) |D=0] as a substitute to the counterfactual mean for those being treated, E[Y (0) |D =1] is possible, but this is unsatisfactory especially in non-experimental studies, because it is likely that components which determine the treatment decision also determine the outcome variable of interest. In our particular case, variables that determine household's participation in the SARD-SC wheat project could also affect household's wheat yield and food security. Therefore, the outcomes of individuals from the treatment and comparison group would differ even in the absence of treatment, leading to a self-selection bias. However, by rearranging and subtracting E[Y (0)|D =0] from both sides of equation 2, ATT can be specified as:

$$\boldsymbol{E[Y(1)|D = 1] - E[Y(0)|D = 0] = \tau_{ATT} + E[Y(0)|D = 1] - E[Y(0)|D = 0]} \quad \textbf{(3)}$$

In equation 3, both terms in the left-hand side are observables and ATT can be identified if there is no self-selection bias, that is if, and only if, E[Y (0) |D =1] - E[Y (0) |D =0] =0. However, this condition can only be ensured in randomized experiments (when there is no self-selection bias). Therefore, some identified assumptions must be introduced for non-experimental studies to solve the selection problem. Basically, there are two strong assumptions available: the Conditional Independence Assumption (CIA) and the Common Support Condition (CSC). The CIA is given as:

$$\boldsymbol{Y_0 Y_1} \perp \frac{\boldsymbol{D}}{\boldsymbol{X}}, \forall \boldsymbol{X}, \tag{4}$$

Where ⊥ indicates independence, X -is a set of observable characteristics, Y 0 -non-participants andY1 –participants. Given a set of observable covariates (X) which are not affected by treatment (in our case, participation in the SARD-SC wheat project), potential outcomes (wheat yield, food security and poverty reduction) are independent of treatment assignment (that is independent of how the households were selected for the project). The implication of CIA assumption is that selection was solely based on observable characteristics (X) and variables that influence treatment assignment (participation in the project) and potential outcomes (wheat yield, food security and poverty reduction) were simultaneously observed (Bryson et al., 2002; Caliendo and Kopeinig, 2005). Hence, after adjusting for observable differences, the mean of the potential outcome is similar for D = 1 and D = 0. Therefore, $E(Y_O/D = 1, X) = E(Y_O/D = 0, X)$.

Imposing a Common Support Condition CSC) ensures that any combination of characteristics observed in the treatment group can also be observed among the control group (Bryson et al, 2002).

Based on the above two assumptions, the PSM estimator of ATT can be written as:

$$\boldsymbol{\tau_{ATT}} = \boldsymbol{E}[\boldsymbol{Y_1} - \boldsymbol{Y_0} | \boldsymbol{D} = \boldsymbol{0}, \boldsymbol{p}(\boldsymbol{x})] = \boldsymbol{E}[\boldsymbol{Y_1} | \boldsymbol{D} = \boldsymbol{1}, \boldsymbol{p}(\boldsymbol{x})] - \boldsymbol{E}[\boldsymbol{Y_0} | \boldsymbol{D} = \boldsymbol{0}, \boldsymbol{p}\ (\boldsymbol{x})] \tag{5}$$

Where P(x) is the propensity score computed on the covariates X. The above equation shows that the PSM estimator is the mean difference in outcomes over the common support, appropriately weighted by the propensity score distribution of participants.

Difference-in-Difference (DID)

The DID model can be specified as:

$$\boldsymbol{Y_i} = \boldsymbol{\alpha} + \boldsymbol{\beta T_i} + \boldsymbol{\gamma t_i} + \boldsymbol{\delta}(\boldsymbol{T_i}.\boldsymbol{t_i}) + \boldsymbol{\varepsilon_i} \tag{6}$$

Where Yi is wheat yield of the sample household, α, β, γ, δ, are unknown parameters to be estimated, εi is a random, unobserved error term which contains all determinants of Yi which the model omits. Here α, represents a constant term while β represents the treatment group specific effect (to account for average permanent differences between treatment and control), γ stands for time trend common to control and treatment groups, and δ represents the true effect of treatment. Unlike the PSM method which used observed covariates to generate the propensity score, the covariates and other unobserved individual specific variables are assumed to be time invariant (unchanged over time). In doing this, the DID method controls not only observed time invariant but also unobserved time invariant variables (Gertler et al., 2016).

Before using the DID method, it is important to check the validity of the underlying assumption of parallel trend assumption. Although there is no way to prove this, the validity of the parallel trend assumption can be tested in different ways. One is to compare changes in outcome for the treatment and for the control groups before the implementation of the program and visually evaluate parallel trends. This needs at least two serial observations prior to the intervention. The second method is to conduct a Placebo test, by performing additional DID estimation using either fake treatment, outcome variable, or a control group (Gertler et al., 2016). The researcher needs to take care to choose which variable can be used as fake treatment, outcome or control group. In our case, the intervention is to boost yield (productivity) through improving dissemination of improved seeds along with improved agronomic practices through an innovation platform. Wheat area is related to wheat yield since yield is obtained as wheat production divided by wheat area. However, wheat area is not affected by the intervention because the intervention focused on technology utilization to boost yield. Hence, wheat area was used as a fake outcome variable.

The equation used for the purpose of the Placebo test is indicated in equation (7).

$$\boldsymbol{A_i = \alpha + \beta T_i + \gamma t_i + \delta(T_i . t_i) + \varepsilon_i} \qquad \textbf{(7)}$$

Where Ai is area under wheat crop and all other parameters and variables are as specified in equation (6).

3. Results and Discussion

3.1 Results of the Descriptive Analysis

3.1.1 Demographic characteristics of the sample households

The demographic characteristics of the sample households showed that members of the sample households were about 45 years of age during the baseline survey year 2012 and 49 years during the end-line survey. Members had attended grade three on average and the family size was with three persons (converted to man equivalent) and almost constant over time. The sample households had nearly six livestock (measured tropical livestock units) on average, also constant over the two periods under consideration. On average a household owned 2.3 hectares of land of which nearly one hectare was allocated to wheat; both variables showed a constant trend between the two survey years. There was, however, an increasing trend of wheat production over the two periods for the whole sample, participants and non-participants (Table 2).

Table 2: Demographic and economic variables of households (continuous variables)

Variables included in PSM	Survey year	Beneficiary (N=214)	Non-beneficiary (N=292)	Total (N=506)	T-Value
		Mean (STD)	Mean (STD)	Mean (STD)	
Age of household head	2012	44.8 (10.2)	45 (11.3)	44.9 (10.8)	0.21
	2016	48.8 (10.2)	48.99 (11.2)	48.91 (10.78)	0.85
Education of head	2012	2.9 (3.2)	3.2 (3.3)	3.1 (3.4)	1.06
	2016	2.95 (3.5)	3.26 (3.1)	3.13 (3.32)	0.30
Family labor (ME)	2012	3.3 (1.1)	3.3 (1.3)	3.3 (1.2)	-0.12
	2016	3.42 (1.36)	3.39 (1.23)	3.4 (1.3)	0.77
Livestock (TLU)	2012	6.1 (4.3)	5.5 (3.3)	5.8 (3.7)	-1.6
	2016	6.1 (4.9)	5.6 (3.7)	5.8 (4.2)	0.169
Land owned (ha)	2012	2.3 (1.7)	2.3 (1.3)	2.3 (1.5)	-0.12
	2016	2.2 (1.5)	2.3 (1.4)	2.3 (1.6)	.48
Wheat area (ha)	2012	0.9 (1.6)	0.9 (0.9)	0.9 (1.3)	-0.14
	2016	0.95 (1.6)	0.93 (0.95)	0.94 (1.3)	0.887
Wheat production (kg)	2012	2781 (5573)	2284 (2946)	2494 (4261)	-1.3
	2016	3037 (5669)	2612 (3512)	2792 (4550)	0.3

STD = Standard Deviation, ME = man equivalent TLU = Tropical Livestock Unit

The discrete variables of the sample households indicate that most of the sample households were headed by males (94%), and had access to extension services with 94% of the sample households reported to have access in 2012 though this decreased to 90% in 2016 with significant differences in proportion between the participating and non-participating households. The case was similar for access to credit which showed a declining trend compared to the baseline for all categories as well as for the whole sample. There were with significant differences between participants and non-participants in 2016 compared to insignificant differences in the baseline survey. However, the proportion of sample households which owned mobiles showed an increasing trend with no significant difference between participants and non-participants in both years.

Table 3: Gender, institutional and communication variables of households (discrete variables)

Discrete variables	Year of survey	Beneficiary (N=214)		Non-beneficiary (N=292)		Total (N=506)		χ^2
		Freq.	%	Freq.	%	Freq.	%	
Sex of household head (% Male)	2012	202	94.4	275	94.2	477	94.3	0.01
	2016	202	94.4	275	94.2	477	94.3	0.01
Access to extension (%Yes)	2012	200	93.5	275	94.2	475	93.9	0.11
	2016	201	93.5	255	87.3	456	90.1	6.0***
Access to credit (%Yes)	2012	132	61.7	182	62.3	314	62.1	0.02
	2016	93	43.5	82	28.1	175	34.6	12.9***
Mobile ownership (%Yes)	2012	126	58.9	161	55.1	287	56.7	0.7
	2016	132	61.7	175	59.9	307	60.7	0.7

3.1.2 Wheat yield

Table 4 presents wheat yield (ton/ha) of sample households in the 2012/13 and 2015/16 cropping seasons. The results indicated that yield of the beneficiaries (participants) at all of the IP sites was significantly higher than the non-beneficiaries in 2016 while it was significantly lower for the overall sample in

2012 with the exception of Enemay and Sinana where farmers who participated in the project already had higher yields than nonparticipants, indicating that the intervention had brought a significant positive effect on participants' wheat yield. There was, however, a variation in yield among the IP sites, with the highest yields reported by participants of the Sinana IP site in Oromia regional state and the lowest among non-beneficiaries of the Gedebano Gutazer Welene (GGW) district of Gurage zone of the SNNP regional state.

Table 4: Wheat yield (ton/ha) of sample households, in 2012/13 and 2015/16

District	Category	N	Year 2016		Year 2012	
			Mean (SD)	P-value	Mean (SD)	P-value
Enemay	Beneficiary	42	2.18 (1.1)	0.005***	2.14 (1.33)	0.001***
	Non-beneficiary	56	1.62 (0.82)		1.45 (0.71)	
Shebel-Berenta	Beneficiary	47	1.82 (0.57)	0.037**	1.5 (0.86)	0.479
	Non-beneficiary	40	1.5 (0.85)		1.39 (0.49)	
Sinana	Beneficiary	29	3.74 (0.84)	0.037**	3.53 (0.99)	0.000***
	Non-beneficiary	67	3.18 (1.31)		2.75 (1.00)	
Gololcha	Beneficiary	34	3.6 (0.93)	0.034**	3.69 (1.2)	0.283
	Non-beneficiary	46	3.1 (1.11)		3.39 (1.25)	
GGW	Beneficiary	23	2.7 (1.1)	0.000***	1.55 (0.94)	0.695
	Non-beneficiary	31	1.2 (1.0)		1.44 (1.0)	
Ofla	Beneficiary	39	2.53 (0.65)	0.007***	2.15 (0.86)	0.535
	Non-beneficiary	52	1.97 (1.13)		2.26 (0.93)	
Total	Beneficiary	214	2.66 (1.11)	0.000***	2.37 (1.34)	0.110
	Non-beneficiary	292	2.22 (1.31)		2.19 (1.19)	

/* means significant at 5% and 1% level of significances, respectively.

3.1.3 Household Food Insecurity Access Scale (HFIAS)

The impact of the intervention on the level of food security of the sample households is presented in Table 5. The result shows that the proportion of the overall sample households categorized in the food secured group of the participants was significantly higher (49 %) than non-participants (45%). Likewise, the proportion of participating sample households categorized as mildly food insecure was also higher (18 %) than the non-participants (11%). However, the proportion of participating sample households categorized as moderately food insecure (20%) was significantly lower than non-participants (28%). Similarly, the proportion of participating households categorized as severely food insecure was lower (13%) than participants (16%) implying that the intervention had produced a positive impact on the food security status of participants in the study sites. Our results are in line with those of Bekele et al (2014) who reported that technology adoption has had a positive impact on food security in Ethiopia.

Table 5: Food security status of the participants and non-participants

Category	Particulars	Food secured	Mildly food insecure	Moderately food insecure	Severely food insecure	Total
Non-beneficiary	Number	131	33	81	47	292
	Percent	45	11	28	16	100
Beneficiary	Number	105	39	42	28	214
	Percent	49	18	20	13	100
Total	Number	236	72	123	75	506
	Percent	47	14	24	15	100

Pearson chi2 (3) = 8.7273 Pr = 0.033

3.1.4 Progress out of Poverty Index (PPI)

One of the objectives of the wheat project intervention was to contribute to poverty reduction by improving livelihoods of participants. Table 6 presents the overall level of the sample households' progress out of poverty. The sample households falling under the poverty line before the intervention (2012) and after implementation of the project (2016) were compared. The results indicated that there was no significant difference between the participating and non-participating households at the end of the intervention period (p = 0.271). However, they clearly showed that participating households have been getting out of poverty at the rate of 0.52%, while non-participating households worsened at the rate of 1.7%. This was a significant difference at 10% implying that there was an improvement of the households participating in the project in terms of the progress out of poverty.

Table 6: Progress out of poverty index (PPI) of the overall sample households, 2016

Particulars	Category	N	Mean	Std. Dev.	p-value
Population living under povert line 2012 (1.25$/day)	Beneficiary	214	43.10	22.09	0.976
	Non-beneficiar	292	43.16	21.90	
Population living under povert line 2016 (1.25$/day)	Beneficiary	214	42.58	20.03	0.271
	Non-beneficiar	292	44.86	21.32	
Change in poverty level (2012 minus 2016)	Beneficiary	214	0.52	12.47	0.051*
	Non-beneficiar	292	-1.69	12.66	

*means significant at 10% level of significance.

3.2 Econometric results

3.2.1 Estimation of propensity scores

The logistic regression model was used to estimate propensity scores for matching treatment households (those participating in the wheat project) with control households (non-participants). As specified above, the dependent variable in this model is binary, indicating whether the household was a participant in the project which takes a value of 1 and 0 otherwise. The analysis was done using STATA 13 computing software using the propensity scores' matching algorithm with psmatch2 installed in the program.

Table 7 shows the intervention participation estimation results of the logistic model of the period sample of 1012 (506 each in 2012 and 2016). The pseudo-R2 value of the estimated model result is 0.0272 which is distinctly low, indicating that the allocation of the project has been fairly random (Pradhan and Rawlings, 2002). The result suggests that participating households did not have diverse characteristics overall and hence obtaining a good match between participating and non-participating households was therefore easier. The estimated coefficient results indicated that participation in the project was significantly influenced by six explanatory variables, namely: education of household head, livestock ownership, wheat area, land holding, level of wheat produced and access to credit. The result indicated that the project targeted households who were significantly less educated, with larger livestock holdings, better access to credit, and with smaller total land holdings as well as wheat land but producing significantly higher potential for wheat production.

Table 7: Logit results of household program participation

Variables	Coefficients	Std. Err.	Z-values	P-values
Constant	-0.623	0.457	-1.36	0.173
Sex of household head	-0.044	0.268	-0.16	0.870
Age of household head	-0.002	0.007	-0.27	0.785
Education of head (completed grade)	-0.059	0.023	-2.59	0.010***
Family labor (Man Equivalent)	0.001	0.057	0.01	0.992
Livestock in (TLU)	0.055	0.021	2.63	0.008***
Wheat area (ha)	-0.741	0.218	-3.4	0.001***
Land owned (ha)	-0.118	0.063	-1.89	0.059*
Wheat production (Kg)	0.0002	0.0001	3.79	0.000***
Access to extension dummy (1=Yes, 0=No)	0.343	0.254	1.35	0.177
Access to credit dummy (1=Yes, 0=No)	0.293	0.138	2.12	0.034**
Mobile ownership dummy (1=Yes, 0=No)	0.043	0.147	0.29	0.770
Year 2016 dummy	0.094	0.141	0.67	0.505
Sample size (N) of two periods = 1012, LR chi2(12) =37.48 Log likelihood = -670.02				
Prob> chi2=0.0002, Pseudo-R2 =0.0272				

and * mean significant at 5% and 1% level of significances, respectively.

Matching participant and comparison households

Before conducting the matching task itself, we carried out the necessary tasks required for PSM techniques: estimating the predicted values of program participation (propensity scores) for all households in or outside the program; imposing a common support condition on the propensity score distributions of household within and without the project; taking the decision to discard observations whose predicted propensity scores fell outside the range of the common support region; and finally conducting sensitivity analysis in order to check the robustness of the estimation (to evaluate whether hidden bias might affect the estimated ATT).

As shown in Table 8, the estimated propensity scores vary between 0.205 and 0.886 (mean = 0.441) for project participants or treatment households and between 0.087 and 0.799 (mean = 0.406) for non-participants (control) households. The common support region lies between 0.205 and 0.799 (the minimum of the treated and the maximum of the control groups). In other words, households whose estimated propensity scores are less than 0.205 and greater than 0.799 were not considered for the matching exercise. As a result of this restriction, 12 households from the two periods (3 project and 9 control households) were discarded from the analysis due to their being out of common support region.

Table 8: Distribution of estimated propensity scores

Group	Observation	Mean	Std. Dev	Minimum	Maximum
Treated households	426	0.441	0.089	0.205	0.886
Control households	586	0.406	0.094	0.087	0.799
Total households	1012	0.421	0.094	0.087	0.886

Choice of matching algorithm

Alternative matching estimators were tried to match the treatment and control households in the common support region. The final choice of a matching estimator was guided by several different criteria including equal means test, referred to as the balancing test (Dehejia and Wahba, 2002), pseudo-R2 and matched sample sizes. A matching estimator which balances all explanatory variables (and results in insignificant mean differences between the two groups), bears a low R2 value and results in large matched sample size, is preferable.

Following Caliendo and Kopeinig (2005) matching quality was tested. Specifically, Caliper matching with 0.1, 0.25 and 0.5; kernel matching with band width of 0.1,0.25 and 0.5; and Nearest Neighbor matching (NNM) ranging from 1 to 5 neighbors were tested. It was found that kernel matching with a band width of 0.1 was the best estimator for the data at hand. Hence, estimation results and discussion are the direct outcomes of the kernel matching algorithm based on a band width of 0.1. Kernel matching associates the outcome of the treated household with the matched outcome that is given by a kernel-weighted average of all control groups (non-beneficiaries) for wheat project intervention. Since the weighted averages of all wheat project interventions in the control group are used to construct the counterfactual outcome, kernel matching has an advantage of lower variance because more information is used (Heckman et al., 1998).

Testing the balance of propensity score and covariates

Once the best performing matching algorithm is chosen, the next task in PSM technique is to check the balancing of propensity score and covariate using different procedures by applying the selected matching algorithm (here kernel matching with band width 0.1). Different testing methods can be used to assess the balancing powers of the estimations, most commonly a reduction in the mean standardized bias between the matched and unmatched households, or equality of means using t-test and chi-square test for joint significance for the variables used. The test results suggested the assumption of the model held (not presented for the sake of precision) and the ATT for the sample households could be estimated.

Estimating the treatment effect and sensitivity analysis of the significant outcomes

Table 9 presents the average treatment effect on treated (ATT) of the intervention of wheat technology adoption through a dissemination IP approach on wheat yield in Kg/ha. The result showed that the average yield of the participants (treated) was 2497 Kg/ha while that of non-participants (control) was 2294 Kg/ha, which is significant at 1% (T-value =2.53). The result previously presented in the descriptive analysis was confirmed using an econometric model, both suggesting that the intervention brought a significant positive impact on the yield of the beneficiaries in the project IP sites. This result is in line with a previous study conducted by Tesfaye et al (2016) who found a positive impact from wheat technology adoption and Berhe (2016) who reported a positive impact on wheat yield in Ethiopia, and Takam-Fongang et al (2018) who found a positive impact from improved variety adoption on maize yield in Cameroon. Our results are also in line with the recent finding of Abate et al (2018) on the impact of the use of new technologies on farmers' wheat yields in Ethiopia using a randomized control trial that reported that full package technology adoption had more impact on wheat yield.

Table 9: Impact of the participation in wheat technology adoption on wheat yield (Kg/ha)

Sample	Treated	Controls	Difference	S.E.	T-stat
Unmatched	2515.84	2204.04	311.80	79.32	3.93***
ATT	2497.22	2293.53	203.69	80.62	2.53***
ATU	2215.87	2399.23	183.37	.	.
ATE			191.96	.	.

***means significant at 1% probability level.

ATT= average treatment effect on the treated; ATU= average treatment effect on the untreated; ATE = average treatment effect

Sensitivity analysis for significant outcome variables

In order to control for unobservable biases, a sensitivity analysis of the wheat intervention on wheat yield was conducted. Table 10 shows the result using the Rosenbaum bounding approach. The critical level of e^{γ}, which gives the causal inference of significant wheat project outcome to be questioned, is presented in the first row.

Since the impact of the project is positive for wheat yield, only the upper bounds have been reported in this study. As Becker and Caliendo (2007) note, assuming the true treatment effect has been underestimated, and reporting the lower bounds are less interesting. Rosenbaum bounds were therefore calculated for a wheat yield outcome that was positive and significantly different from zero (Rosenbaum, 2002). The outcome variable (wheat yield) is listed in the first column while the rest of the values which correspond to this row were p-critical values (or the upper bound of Wilcoxon significance level -Sig+) at different critical value of e^{γ} .

The result shows that the inference for the effect of the wheat project interventions was not changing though the participants and non-participant households were allowed to differ in their odds of being treated up to 150% (2.5) in terms of unobserved covariates. That means, for the outcome variable (yield) estimated, at various level of critical value of e^{γ} ranging from 1 to 2.5, that the p-critical values were significant, further indicating that important covariates, affecting both participation and outcome variables, had been considered. The sensitivity analysis result showed that there was no critical value of e^{γ} where the estimated average treatment effect on the treated (ATT) was questioned, even if the larger values up to 2.5 were set, and this was a larger value than that normally found in the literature, usually 2 (100%). It can, therefore, be concluded that the impact estimates (ATT) of this study were insensitive to unobserved selection bias and purely the effect of the wheat project interventions implemented in the project IP sites.

Table 10: Result of sensitivity analysis using Rosenbaum bounding approach (upper bounds)

Outcomes	$e^{\gamma}=1$	$e^{\gamma}=1.25$	$e^{\gamma}=1.5$	$e^{\gamma}=1.75$	$e^{\gamma}=2$	$e^{\gamma}=2.25$	$e^{\gamma}=2.5$
Yield	P<0.000	P<0.000	P<0.000	P<0.000	P<0.000	P<0.000	P<0.000

e^{γ} (Gamma)=log odds of differential due to unobserved factors where Wilcoxon significance level for each significant outcome variable is calculated

3.2.2 Result of Difference-in-Difference (DID) method

Before rushing into estimating the DID, a Placebo test was conducted using the wheat area as a 'fake' outcome variable to check for the validity of the parallel trend assumption of the DID method. The test result indicated that there was no evidence for rejecting the parallel trend assumption as indicated by an insignificant p=0.686 and coefficient of the interaction term between year 2016 dummy and participation of 0.05 (not reported), confirming that the parallel trend assumption held when the coefficient was zero or near to zero. Therefore, using the DID method, like the PSM, was valid for the data at hand. However, rather than using a standard DID method involving the whole sample, a modified DID using only matched samples (1000 instead of 1012) was used to evaluate the impact under the modified scenario. Table 11 presents the result of DID under both scenarios. The result shows that participating sample households had 235kg/ha more yield than non-participating households based on the matched sample households with insignificant difference, and 262 kg/ha more yield than non-participating households based on the unmatched whole sample. This gives a significant difference at 10% probability level.

Table 11: DID result of impact of adoption of wheat technology via IP dissemination approach

	DID with whole sample (1012)			DID with matched samples (1000)		
Wheat yield	**Coef.**	**Std. Err**	**p>t**	**Coef.**	**Std. Err**	**p>t**
Year2016 dummy	26	103	0.801	367	103.	0.722
Participation	180	112	0.108	164	112	0.144
Year 2016* participation	262	158	0.099	235	159	0.139
Constant	2191	72	0.000	2198	73	0.000

4. Conclusion and Recommendations

4.1 Conclusion

This study investigated the impact of a new approach to technology adoption using an innovation platform dissemination approach on yield, food security and poverty in the major wheat producing regions of Ethiopia. The result showed that the intervention brought a significant positive impact for the wheat yield of participating households. The result of the DID model showed that the participating households obtained more 235kg/ha wheat compared to non-participants at the end of the project period. The intervention was also found to have a significant positive impact on food security and poverty reduction. To sum up, this study provides empirical evidence that interventions on promotion and dissemination of available technology through innovative methods such as IP approaches can make a positive impact on yields, food security and poverty reduction. A strategic innovation platform with best fit agricultural technologies would be effective for sustainable technology transfer and impact.

4.2 Recommendation

Based on the findings of this study, we would recommend shifting from the linear technology dissemination approach to an innovation platform approach under which farmers, extension workers, agriculture experts and subject matter specialists can come together, and receive training and experience sharing to help technology adoption to provide for higher levels of impact on yield and other aspects of farm household well-being.

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Appendix

Table 1: Questions set for indicator of poverty

How many people are in the HH?
Do all children ages 6 to 12 attend school?
Excluding kitchen and toilets, how many rooms
What is the main construction material of the
What type of toilet facility does the HH use?
What is the main source of cooking fuel?
Does the HH currently own any mattresses and/
Does the HH currently own any radio?
Does the HH currently own any watches or clock
Does the HH currently own any cattle, sheep,
Does the HH currently own any jewellery (gold

Table 2: Estimated poverty likelihoods associated with scores: ($1.25/day 2005 PPP line)

If a household's score is…	then the likelihood (%) of being below the poverty line is:
0-4	87.6
5-9	82.9
10-14	63.6
15-19	58.3
20-24	47.7
25-29	38.5
30-34	28.4
35-39	18.5
40-44	18.4
45-49	18.6
50-54	7.4
55-59	5.0
60-64	3.0
65-69	2.2
70-74	0.5
75-79	1.1
80-84	3.4
85-89	9.3
90-94	0.0
95-100	0.0