Greener Journal of Agricultural Sciences
Vol. 9(1), pp. 76-85, 2019
ISSN: 2276-7770

DOI Link: http://doi.org/10.15580/GJAS.2019.1.122118180
http://gjournals.org/GJAS

Impact of Improved Wheat Technology Package Adoption on Productivity in Ethiopia

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ARTICLE INFO

Article No.: *122118180*
***Type*:** *Research*
DOI: *10.15580/GJAS.2019.1.122118180*

Submitted: *21/12/2018*
Accepted: *27/12/2018*
Published: *06/03/2019*

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Keywords: *impact; wheat; improved technology package; Ethiopia*

ABSTRACT

This study examines the impact of adoption of improved wheat technology package (including improved wheat varieties, information regarding improved wheat management practices as well as artificial/chemical fertilizer) on productivity using 1,611 sample farm households in four major administrative regions of Ethiopia. Propensity score matching (PSM) technique was employed since it is an increasingly utilized standard approach for evaluating impacts using observational data of a single period. It is found that full adoption of improved wheat technology package appears to significantly increase productivity growth on the average by 51 to 55% for farm households in the study area. Thus, the study recommends that full adoption of improved wheat technology package could be an effective strategy to enhance productivity and, thereby, production that contributes a lot to the structural transformation of the Ethiopian economy.

INTRODUCTION

Like in many other sub-Saharan Africa countries, agriculture in Ethiopia is a basis for the entire socioeconomic structure of the country and has a major influence on all other economic sectors and development processes and hence it plays a crucial role in poverty reduction (Elias *et al*., 2013; GebreEyesus, 2015). Despite the marginal decline in its share of GDP in recent years, it is still the single largest sector in terms of its contribution to GDP as agricultural GDP constitutes 41% of total country's GDP (CSA, 2014/15).

As to Gebru 2006 citing CSA 2003, out of the total production of agriculture, about 70% comes from crop production. According to Abegaz 2011, cereal crops constitute the largest share of farming household's production and consumption activities. Accordingly citing Alemayehu *et al*., 2009, only five major cereals (barley, maize, sorghum, teff and wheat) account for about 70% of area cultivated and 65% of output produced. Fertilizer use is also concentrated on cereals followed by pulses and oilseeds respectively according to Endale 2011 citing CSA 1995/96-2007/08. On the other hand, according to Endale 2011, data from the Ethiopian Seed Enterprise show that improved seeds are mostly used in wheat and maize cultivation with an average of 89 and 42 thousand quintal in the period 1994/95 to 2005/06, respectively. Moreover, Abegaz 2011 citing the Household Income, Consumption and Expenditure Survey of CSA indicated that the five major cereal crops account for 46% of household's total consumption. Therefore, a closer look at what is happening in cereal production has an important welfare and policy implication in Ethiopia (Abegaz, 2011).

According to Ketema and Kassa 2016 citing Shiferaw *et al*. 2013, wheat contributes about 20% of the total dietary calories and proteins worldwide. Ethiopia is the second largest wheat producer in sub-Saharan Africa next to South Africa (Nigussie *et al*., 2015). Mann and Warner 2017 citing Minot *et al*. 2015 indicated that there are approximately 4.7 million farmers growing wheat on approximately 1.6 million hectares representing between 15 and 18% of total crop area and less than 1% of all wheat production takes place outside the four main regions of Ethiopia according to recent estimates. Wheat is one of the major staple crops in the country in terms of both production and consumption (Kelemu, 2017). According to Kelemu 2017 citing FAO 2014, it is the second most important food in the country behind maize in terms of caloric intake.

The Ethiopian agricultural sector, as to Gebru 2006 citing EEA 2004, is dominated by small-scale farmers cultivating about 96% of the total area under crop, producing more than 90% of total agricultural output and 97% of food crops. With these statistics, one can easily infer to what extent the small-scale farmers are the key element in strengthening the effort towards agricultural growth and consequently to the overall economic growth (Gebre-Selassie & Bekele).

On the other hand, most smallholder farmers (i.e. 59% of total cultivated area) reside in the moisture reliable cereal-based highlands among the five agro-ecological regions of Ethiopia distinguished by agricultural researchers (Taffesse *et al*., 2012). Accordingly, with farmers using virtually no irrigation, reliable rainfall is an important condition to achieve good agricultural productivity. In relation to this, as to the same source document, the Meher rainfall season is overwhelmingly important as it contributes about 96.9% of total crop production and 95.5% of total cereal production in 2007/08.

With respect to all these facts, it is not questionable that accelerated and sustained growth in the country's agriculture in general and in the crop sub-sector in particular with special emphasis to the small-scale farmers will greatly help to achieve the various goals of the country (Gebru, 2006; MoFED, 2003; Gebre-Selassie & Bekele).

Moreover, food needs as well as the industrial demand for agricultural products increase due to population growth (Bor and Bayaner, 2009). All these needs, according to them, require an increase in the agricultural production. The growth in agricultural production in sub-Saharan Africa in the past was achieved by expanding the amount of land cultivated (Gebru, 2006). In relation with this, it is well known that in our country there are regions where there are large populations but limited land and vice versa (MoFED, 2003). Accordingly, most of the lands available for settlement are found in the lowlands that lack basic infrastructural facilities and pose serious health hazards. With little suitable land available for expansion of crop cultivation, especially in the highlands, future cereal production growth will need to come from increasing land productivity mainly through the supply, duplication and diffusion of continuously improving technology and information (Ayele *et al*. 2006 citing Reardon *et al* 1996; Taffesse *et al*. 2012; Elias *et al*. 2013; Matsumoto and Yamano, 2010).

Cognizant of these as well as the fact that productivity is the major component of growth and a fundamental requisite in many form of planning irrespective of the stage of development and economic and social system as to Gebru 2006 citing Cheema 1978, the national wheat research program has released and disseminated a number of bread and durum wheat varieties since the 1950s and 1960s as to Ketema and Kassa 2016 citing Tesfaye *et al*. 2001. According to the same source citing CSA 2015b, a closer look at the proportion of the area covered by improved varieties of different crops showed that wheat took the second rank (7.4%) next to maize (46.4%) among cereals. Given the emphasis of increasing crop production through higher fertilizer use, import of chemical fertilizer augmented from 246,722 MT in 1995 to 375,717 MT in 2006 despite the removal of fertilizer subsidies since 1997/98 according to Endale 2011 citing MOARD 2007/08. In this regard, according to Ketema and Kassa 2016 citing CSA

2015b, wheat is the most fertilized crop (82%) among all crops and pesticide application is also most common on wheat as compared to that on other cereal crops.

Even though crop productivity and production remained low and variable in the 90s for the most part, there have been clear signs of change over the past decade (Abate *et al*., 2015). According to Kelemu 2017, the average level of wheat productivity for the period of 2000-2014 is about 1.73 ton/ha while the average growth rate in productivity is about 5.93%. During the same period, total wheat production has been increasing at 10.14% growth rate per annum (Kelemu, 2017).

As to Tsusaka and Otsuka 2013 citing FAO 2011, although the production of staple food has been increasing in sub-Saharan Africa, the rate of increase has not been high enough to outstrip its high population growth rate as a result of which per-capita agricultural production in the region has declined by about 10% since 1960. These all obviously calls for a further and a better growth in agricultural productivity as well as quality with minimum adverse impact on the environment. Kelemu 2017 citing Shiferaw and Okelo 2011 indicated that of the cereals whose production is soon likely to exceed domestic demand requirements, wheat is the commodity that will most easily find an export market to supply. In view of this prospect, according to him, the need for increasing productivity of wheat is very crucial.

Holistic and appropriate evaluation of the efforts and corresponding results as well as reasons/strengths and weaknesses/ of the past few decades in general and of the past recent years in particular is necessary in order to create a more fertile ground for the fast achievement of the aforementioned goal. In this regard, the role of historical data collected by different agencies like CSA as well as of different socio-economic studies carried out to provide vital policy and related recommendations is indispensable. Studies that assess the contribution of improved crop management practices information and technologies like improved crop varieties for the productivity growth of such important and widely cultivated cereals like wheat in Ethiopia in the past recent years are among studies that can be cited in relation to this. However, studies carried out in the country on this issue are not only few but also restricted to piece meal or location specific approach. Besides, most studies were biased towards those locations that had high/better suitability and/or preference for the production of the specific crop considered. Thus, a nationally or regionally representative data could not be collected for the studies and the conclusions drawn so far would have low probability of influencing national and regional policies. Moreover, the focus of most studies was measuring the impact of a single improved agricultural technology or information rather than of a package of agricultural technologies and information. Thus, the objective of this study is to identify the impact of adoption of improved wheat technology package (including improved wheat varieties, information regarding improved wheat management practices as well as artificial/chemical fertilizer) on wheat productivity per unit of land cropped in the four major administrative regions of Ethiopia which are also known to be the major wheat producing regions in the country.

MATERIALS AND METHODS

Analytical Framework for Evaluation of Adoption of Wheat Technology Package Impact on Productivity

The correct evaluation of the impact of a treatment like adoption of a technology package will require identifying the "average treatment effect on the treated" defined as the difference in the outcome variables between the treated objects like farmers and their counterfactual. A counterfactual is defined as "*knowledge of what would have happened to those same people if they simultaneously had not received treatment*" (Olmos A., 2015 citing Shadish *et al*., 2002). In this context, as to González *et al*. 2009, if Y represents the outcome variable and if D is a dummy variable that takes the value of 1 if the individual was treated and 0 otherwise, the "average treatment effect on the treated" will be given by:

$$(1) \qquad T_{ATT} = E[Y(1) / D = 1] - E[Y(0) / D = 1]$$

However, accordingly, given that the counterfactual (E[Y (0) / D = 1]) is not observed, a proper substitute has to be chosen to estimate T_{ATT}. Using the mean outcome of non-beneficiaries-which is more likely observed in most of the cases-do not solve the problem given that there is a possibility that the variables that determine the treatment decision also affect the outcome variables. In this case, the outcome of treated and non-treated individuals might differ leading to selection bias (González *et al*., 2009). To clarify this idea, the mean outcome of untreated individuals has to be added to (1) from which the following expression can be easily derived:

$$(2) \quad T_{ATT} = \{E[Y(1) / D = 1] - E[Y(0) / D = 0]\} - \{E[Y(0) / D = 1] - E[Y(0) / D = 0]\}$$

Here $E[Y(0) / D = 1] - E[Y(0) / D = 0]$ represents the selection bias which will be equal to zero if treatment was given randomly which can be achieved through the use of experimental approach.

The experimental approach, according to Olmos A. 2015, has two characteristics: (1) it manipulates the independent variable, that is, whether an individual receives (or not) the intervention under scrutiny and (2) individuals are randomly assigned to the independent variable. The first characteristic does not define the experimental approach: most of the so-called quasi-experiments also manipulate the independent variable.

What defines the experimental method is the use of random assignment (Olmos A., 2015). However, due to ethical or logistical reasons, random assignment is not possible as to Olmos A. 2015 citing Bonell *et al*. 2009. Moreover, accordingly, equivalent groups are not achieved despite the use of random assignment which is known as randomization failure. Usual reasons why randomization can fail are associated with missing data which happened in a systematic way and sometimes can go undetected (Olmos A., 2015).

As a consequence of randomization failure, or because of ethical or logistical reasons, in a very large number of real-world interventions, experimental approaches are impossible or very difficult to implement. However, if we are still interested in demonstrating the causal link between our intervention and the observed change, our options become limited. Some options include regression discontinuity designs which can strengthen our confidence about causality by selecting individuals to either the control or treatment condition based on a cutoff score. Another alternative is propensity scores matching technique. Propensity scores matching is a statistical technique that has proven useful to evaluate treatment effects when using quasi-experimental or observational data (Olmos A., 2015 citing Austin, 2011 and Rubin, 1983). Some of the benefits associated with this technique, accordingly, are: (a) Creating adequate counterfactuals when random assignment is infeasible or unethical, or when we are interested in assessing treatment effects from survey, census administrative, or other types of data, where we cannot assign individuals to treatment conditions. (b) The development and use of propensity scores reduces the number of covariates needed to control for external variables (thus reducing its dimensionality) and increasing the chances of a match for every individual in the treatment group. (c) The development of a propensity score is associated with the selection model, not with the outcomes model, therefore the adjustments are independent of the outcome. According to Olmos A. 2015, propensity scores are defined as the conditional probability of assigning a unit to a particular treatment condition (i.e., likelihood of receiving treatment), given a set of observed covariates:

$$(z = i \mid X)$$

where z = treatment, i = treatment condition, and X = covariates. In a two-group (treatment, control) experiment with random assignment, the probability of each individual in the sample to be assigned to the treatment condition is: $(z = i \mid X)=0.5$. In a quasi-experiment, the probability $(z = i \mid X)$ is unknown, but it can be estimated from the data using a logistic regression model, where treatment assignment is regressed on the set of observed covariates (the so-called *selection model*). The propensity score then allows matching of individuals in the control and treatment conditions with the same likelihood of receiving treatment. Thus, a pair of participants (one in the treatment, one in the control group) sharing a similar propensity score are seen as equal, even though they may differ on the specific values of the covariates (Olmos A. 2015 citing Holmes 2014).

Data and Variables

The data utilized for this study is acquired from farm household survey undertaken during 2015/16 by Ethiopian Institute of Agricultural Research (EIAR) in collaboration with the International Maize and Wheat Improvement Center (CIMMYT). The sampling frame covered seven major wheat growing agro-ecological zones that accounted for over 85% of the national wheat area and production distributed in the four major administrative regions of Ethiopia- Amhara, Oromia, Tigray as well as South Nations, Nationalities and Peoples (SNNP). A multi-stage stratified sampling procedure was used to select villages from each agro-ecology, and households from each “kebele”/village. First, agro-ecological zones that account for at least 3% of the national wheat area each were selected from all the major wheat growing regional states of the country mentioned above. Second, based on proportionate random sampling, up to 21 villages in each agro-ecology, and 15 to 18 farm households in each village were randomly selected. The data was collected using a pre-tested interview schedule by trained and experienced enumerators who speak the local language and have good knowledge of the farming systems. Moreover, the data collection process was supervised by experienced researchers to ensure the quality of the data.

Productivity stands for the productivity of wheat per unit of land cropped measured in kilogram per hectare.

LnProductivity stands for the natural logarithmic transformation of Productivity.

HHAGE stands for the age of a household head.

HHSEX is a dummy variable indicating the sex of a household head where HHSEX = 1 if the head is male and 0 if otherwise.

FAMILY_SIZE stands for size of a household.

HHEDU is a dummy variable indicating whether a household head is literate where HHEDU = 1 if the head is literate/able to read and write/ and 0 if otherwise.

CREDIT is a dummy variable indicating household's access to credit where CREDIT = 1 if the household has got the credit it needed in 2013 and 0 if otherwise.

LANDHOLDING_SIZE stands for size of the land holding of a household measured in hectare.

DSTMNMKT stands for distance to the nearest main market from residence measured in kilometer.

OXEN stands for the total number of oxen owned by a household.

TNOTRAREDS stands for the total number of traders known by a household who could buy the produced grain.

EXCONTACT is a dummy variable indicating whether a household had contact with government extension workers where EXCONTACT = 1 if the household had got contact with government extension workers and 0 if otherwise.

RESULTS AND DISCUSSIONS

Descriptive Statistics

Various variables that were included in the propensity score matching model that describe the major observed characteristics of the sample respondents are presented in in table 1. While the average productivity of full and partial adopters of modern technologies & information is 1.76 and 1.34 ton per hectare respectively, that of non-adopters of modern technologies & information is only 0.93 ton per hectare. Thus, it tentatively shows that there is significant difference in productivity level between these two pairs of groups of households. Some of the most important demographic determinants that influence adoption of a technology include family size, level of education and age. There exists a significant difference between adopters and non-adopters of wheat technology and information in terms of these demographic factors as depicted by the descriptive statistics. Male-headed households were found to be more probable in adopting improved wheat technology package fully and partially which is in line with the fact that female-headed households are endowed with less resource and are less exposed to new information and ideas according to Admassie and Ayele 2004. Besides, the descriptive statistics show that literate-headed household are more probable in adopting improved wheat technology package fully. This might be because education may make farmers more receptive to advice from an extension agent or more able to deal with technical recommendations that require a certain level of numeracy or literacy (Admassie and Ayele, 2004). On the other hand, households with relatively larger family size are less likely to adopt improved wheat technology package fully and partially which is a bit contradictory to the fact that such households, on one hand, do not face labor shortage that may be needed to manage the increased output which resulted from technology and information adoption and, on the other hand, higher family size necessitates increased productivity to feed the family. Farmers with relatively smaller land holding size tend to adopt improved wheat technology package fully and partially which is in line with the fact that certain technologies may be appropriate for the intensive management characteristic of smaller farms as to Admassie and Ayele 2004. Moreover, those farmers who had contact with government extension workers are more likely to adopt improved wheat technology package fully and partially than those that had not.

Table 1(a): Descriptive statistics of important variables used in the probit model-Propensity score matching

Variables	Unit	Full Adopters of Modern Technologies & Information Mean(se)	Non-Adopters of Modern Technologies & Information Mean(se)	Aggregate Mean(se)	t-stat.
Outcome variable					
Productivity	#	1756.79(30.70)	931.48(214.35)	1750.74(30.58)	-2.305**
LnProductivity	%	7.29(0.019)	6.60(0.248)	7.28(0.019)	-3.16***
Variables that affect probability of adoption					
HHAGE	#	45.50(0.35)	49.89(6.25)	45.53(0.35)	1.06
HHSEX (Male=1)	1=Yes	0.912(0.008)	0.78(0.15)	0.911(0.008)	-1.41*
FAMILY_SIZE	#	6.64(0.064)	8.33(0.93)	6.65(0.064)	2.25**
HHEDU (Read & write=1)	1=yes	0.66(0.014)	0.33(0.17)	0.65(0.014)	-2.03**
CREDIT	1=yes	0.079(0.008)	0(0)	0.078(0.008)	-0.88
LANDHOLDING_SIZE	ha	1.56(0.037)	2.7(0.903)	1.56(0.037)	2.65***
DSTMNMKT	km	9.09(0.172)	9.78(0.662)	9.09(0.171)	0.35
OXEN	#	2.19(0.048)	1.67(0.24)	2.18(0.047)	-0.94
TNOTRAREDS	#	4.45(0.161)	3.33(1.01)	4.44(0.16)	-0.59
EXCONTACT	1=yes	0.89(0.009)	0(0)	0.884(0.0092)	-8.53***

***, **, * indicate significance at 1 percent, 5 percent and 10 percent level respectively.

Source: Own computation, 2018

Table 1(b): Descriptive statistics of important variables used in the probit model-Propensity score matching

Variables	Unit	Partial Adopters of Modern Technologies & Information Mean(se)	Non-Adopters of Modern Technologies & Information Mean(se)	Aggregate Mean(se)	t-stat.
Outcome variable					
Productivity	#	1341.69(42.48)	931.48(214.35)	1332.25(41.88)	-1.47*
LnProductivity	%	7.01(0.034)	6.605(0.248)	6.997(0.034)	-1.77**
Variables that affect probability of adoption					
HHAGE	#	47.24(0.698)	49.89(6.25)	47.30(0.695)	0.57
HHSEX (Male=1)	1=Yes	0.929(0.0131)	0.78(0.147)	0.9258(0.0133)	-1.72**
FAMILY_SIZE	#	6.33(0.108)	8.33(0.93)	6.38(0.108)	2.79***
HHEDU (Read & write=1)	1=yes	0.542(0.0255)	0.33(0.167)	0.537(0.0252)	-1.24
CREDIT	1=yes	0.039(0.00995)	0(0)	0.038(0.0097)	-0.605
LANDHOLDING_SIZE	ha	1.475(0.066)	2.7(0.903)	1.503(0.0685)	2.70***
DSTMNMKT	km	8.94(0.283)	9.78(0.662)	8.96(0.277)	0.455
OXEN	#	1.79(0.091)	1.67(0.236)	1.78(0.089)	-0.2
TNOTRAREDS	#	3.91(0.248)	3.33(1.014)	3.9(0.243)	-0.36
EXCONTACT	1=yes	0.675(0.024)	0(0)	0.6598(0.024)	-4.32***

***, **, * indicate significance at 1 percent, 5 percent and 10 percent level respectively.
Source: Own computation, 2018

Propensity Scores Estimation using Probit Model

The descriptive statistics of the key variables affecting adoption of improved wheat technology package has shown a tentative impact of improved wheat technology package adoption on increasing productivity. Nevertheless, a mere comparison of productivity has no causal meaning since improved wheat technology package adoption is endogenous. And it is difficult to attribute the change to adoption of improved wheat technology package since the difference in productivity might be owing to other determinants. To this end, a rigorous impact evaluation method; namely, Propensity Score Matching has to be employed to control for observed characteristics and determine the actual attributable impact of improved wheat technology package adoption on productivity in wheat producing areas of Ethiopia. Propensity scores for full adopters and non-adopters as well as for partial adopters and non-adopters were estimated using a probit model to compare the treatment group with the control group. In this regard, only those variables that significantly affect probability of full and partial improved wheat technology package adoption were used in estimating the propensity scores. The test for 'balancing condition' across the treatment and control groups was done and the result as indicated on figure 1 proved that the balancing condition is satisfied.

Each observation's propensity scores are calculated using a probit model. The propensity score for full adopters ranges between 0.591009 and 0.9997821 while it ranges between 0.58267 and 0.978982 for non-adopters. And the region of common support for the distribution of estimated propensity scores of full adopters and non-adopters ranges between 0.59100901 and 0.99978208. When matching techniques are employed, observations whose propensity score lies outside this range were discarded. The visual presentation of the distributions of the propensity scores is plotted in figure 1(a). The common support condition is satisfied as indicated by the density distributions of the estimated propensity scores for the treatment and control groups as there is substantial overlap in the distribution of the propensity scores of both full adopters and non-adopters. On the other hand, the propensity score for partial adopters ranges between 0.5600793 and 0.9945421 while it ranges between 0.8195451 and 0.9729395 for non-adopters. And the region of common support for the distribution of estimated propensity scores of partial adopters and non-adopters ranges between 0.56007927 and 0.99454209. When matching techniques are employed, observations whose propensity score lies outside this range were discarded. The visual presentation of the distributions of the propensity scores is plotted in figure 1(b). The common support condition is satisfied as indicated by the density distributions of the estimated propensity scores for the treatment and control groups as there is substantial overlap in the distribution of the propensity scores of both partial adopters and non-adopters.

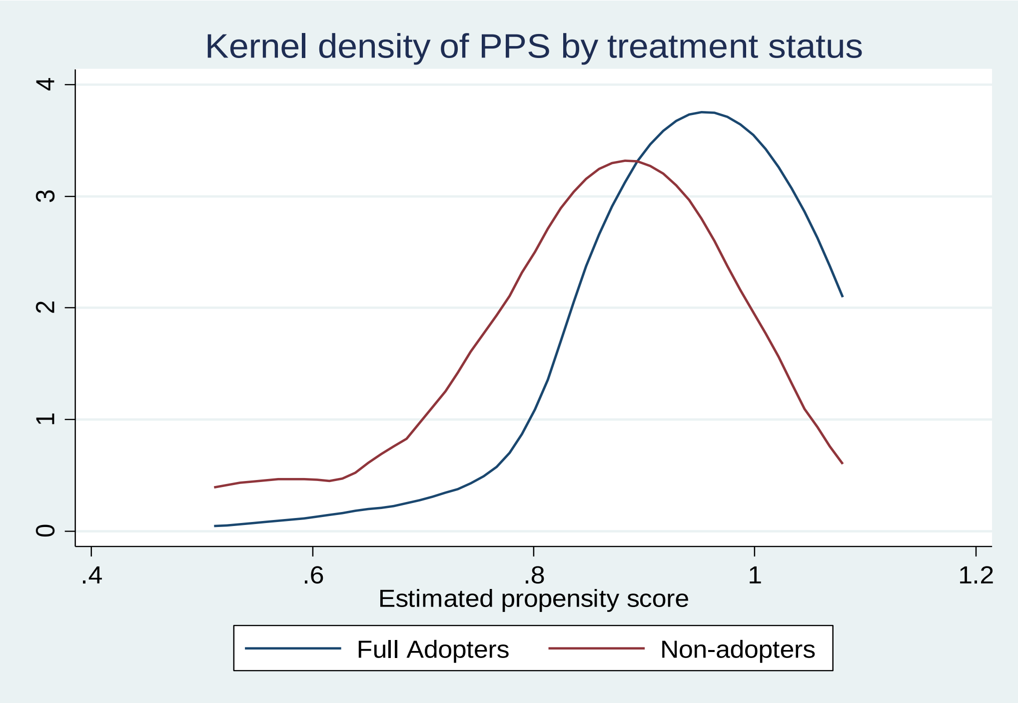

Figure 1(a): Distribution of propensity scores of full adopters and non-adopters

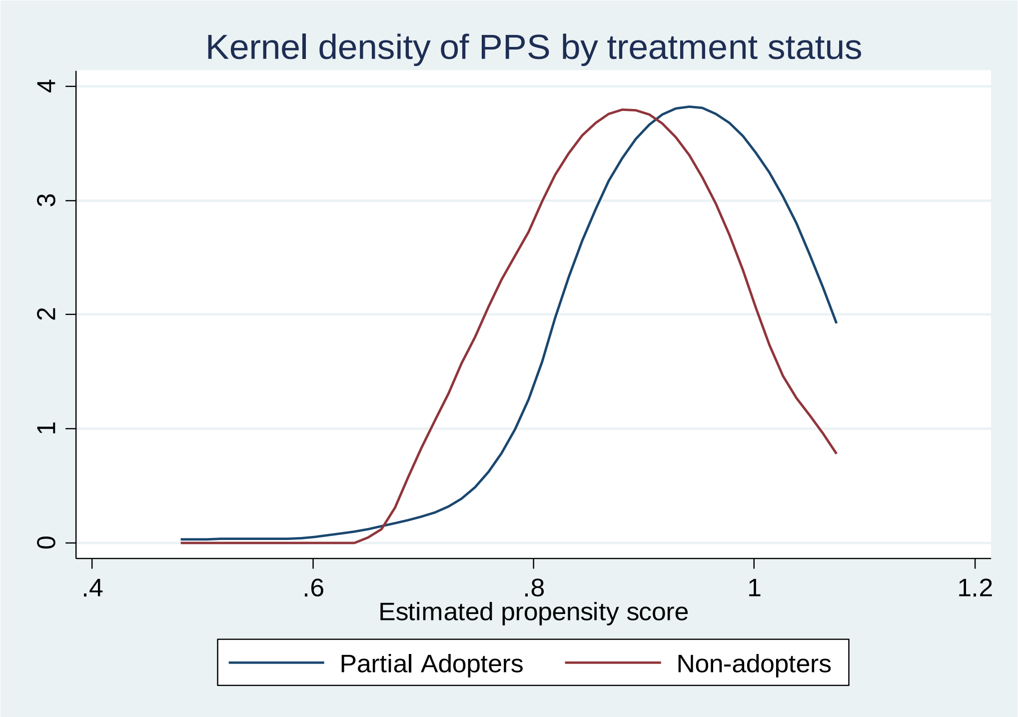

Figure 1(b): Distribution of propensity scores of partial adopters and non-adopters

Assessing Matching Quality

Ensuring good balance between treated and control group is the most important step in using any propensity score method. The before and after matching covariate balancing tests presented on table 2 suggested that the proposed specification of the propensity score is fairly successful in balancing the distribution of covariates between the two groups as indicated by decreasing pseudo R^2 for the partial adopters vs. non-adopters case, decreasing mean standardized bias and the insignificant p-values of the likelihood ratio test.

Table 2(a): Propensity score matching quality test

Sample	Ps R2	LR chi2	p>chi2	Meanbias	Medbias	R	%Var
Unmatched	0.163	10.94	0.027	122.4	66.3	1.37	100
Matched	0.203	75.47	0.000	49.2	51.4	2.36*	100

* if B>25%, R outside [0.5; 2]

Table 2(b): Propensity score matching quality test

Sample	Ps R2	LR chi2	p>chi2	Meanbias	Medbias	R	%Var
Unmatched	0.097	6.41	0.093	93.3	63.6	1.19	100
Matched	0.080	27.50	0.000	19.5	21.1	2.51*	50

* if B>25%, R outside [0.5; 2]

Average treatment effects estimation

Different impact estimators were employed to get estimated treatment effect that disclosed full as well as partial adoption of improved wheat technology package has a positive and significant impact on productivity growth. Table 3 depicts the average impact of improved wheat technology package adoption on productivity growth following nearest neighbor matching (NNM), Stratification Matching, Radius (Caliper) Matching and Kernel Matching (KM) techniques. Accordingly, most of the matching techniques revealed that on the average full adopters of improved wheat technology package get a significantly higher rate of growth in productivity, ranging from 51 to 55%, than their counterparts, the non-adopters. Moreover, half of the matching techniques revealed that on the average partial adopters of improved wheat technology package get a significantly higher rate of growth in productivity, ranging from 38 to 51%, than their counterparts, the non-adopters. However, the growth rate of full package adopters that includes improved wheat varieties, information regarding improved wheat management practices as well as artificial/chemical fertilizer is clearly higher than that of the partial package adopters.

Table 3(a): Average treatment effects estimation using different propensity score matching estimators

Outcome variable	Matching algorithm	Mean of outcome variable based on matched observations		ATT	t-stat.
		Full Adopters	Non-Adopters		
LnProductivity	Nearest neighbor matching	7.17	6.62	0.548	1.439*
	Stratification matching			0.394	.
	Caliper matching	6.92	6.53	0.388	1.035
	Kernel matching	7.17	6.66	0.508	2.181**

**, * indicate significance at 5 percent and 10 percent level respectively.
Bootstrapped standard errors are based on 100 replications.
Source: Own computation, 2018

Table 3(b): Average treatment effects estimation using different propensity score matching estimators

Outcome variable	Matching algorithm	Mean of outcome variable based on matched observations		ATT	t-stat.
		Partial Adopters	Non-Adopters		
LnProductivity	Nearest neighbor matching	7.01	6.59	0.428	1.209
	Stratification matching			0.226	0.858
	Caliper matching	7.36	6.84	0.514	1.605*
	Kernel matching	7.01	6.63	0.383	1.836**

**, * indicate significance at 5 percent and 10 percent level respectively.
Bootstrapped standard errors are based on 100 replications.
Source: Own computation, 2018

CONCLUSION AND RECOMMENDATION

This study is undertaken to identify the impact of adoption of improved wheat technology package that includes improved wheat varieties, information regarding improved wheat management practices as well as artificial/chemical fertilizer on wheat productivity in Ethiopia. It used propensity score matching technique which is a robust impact evaluation technique that identifies the impact which can be attributed to improved wheat technology package adoption. The study also employed and compared various matching algorithms to ensure robustness of the impact estimates. Finally, the study concludes that adoption of improved wheat technology package enabled farm households that adopted it fully to enjoy a relatively higher and significantly positive productivity than their counterparts, the non-adopters as well as the partial adopters. This indicates that full adoption of improved wheat technology package has a huge potential in strengthening the country's agricultural extension system that targets increasing production and productivity. Therefore, this study recommends to widely scale-up full package of improved wheat varieties and information as well as other appropriate modern agricultural technologies and information to all wheat producing farm households, and this should be accompanied by increasing availability of affordable improved wheat agricultural technologies and information for the smallholder farmers to enhance their livelihood which obviously calls for the well-coordinated, effective as well as efficient effort of all of the relevant stakeholders of the agricultural sector of the country.

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Cite this Article: Baye B; Fitsum D; Eyob B (2019). Impact of Improved Wheat Technology Package Adoption on Productivity in Ethiopia. Greener Journal of Agricultural Sciences 9(1): 76-85, http://doi.org/10.15580/GJAS.2019.1.122118180.