

# Impact of Improved Technology Package Adoption on Maize Yield Growth in Ethiopia: Conditional Differences in Differences Approach Application

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## Abstract

This study examines the impact of adoption of improved maize technology package (including improved maize varieties, fertilizer of any kind as well as row planting) on maize yield growth of Ethiopia at national level. In so doing, a balanced panel data set covering two time periods was used and propensity score matching in combination with a difference-in-differences estimator was employed to better match control and project units on preprogram observable characteristics and to control for certain types of unobserved variables which can be assumed to remain fixed over a shorter time series. It is found that that adoption of improved maize technology package had positive and significant impact on maize yield growth of Ethiopia at national level. Therefore, this study recommends to widely scale-up the efficient use of improved maize varieties in combination with other complementary inputs and agronomic practices to all maize producing farm households which obviously calls for embracing the enormous diversity of the production systems as well as a well-coordinated, effective as well as efficient effort of all of the relevant stakeholders of the agricultural sector of the country including farmers supported with a major recommitment to effective overall management of so many facets of the economic environment.

**Keywords:** Impact, Maize, Improved Varieties, Fertilizer, Row Planting, Ethiopia

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## 1. Introduction

Roughly 80 percent of Africa's poor live in rural areas, and even those who do not will depend heavily on increasing agricultural productivity to lift them out of poverty (Haggblade, 2004). Accordingly, seventy percent of all Africans—and nearly 90 percent of the poor—work primarily in agriculture. As consumers, all of Africa's poor—both urban and rural—count heavily on the efficiency of the continent's farmers. Farm productivity and production costs largely determine the prices of basic food stuffs, which account for 60–70 percent of total consumption expenditures by low-income groups (Haggblade, 2004). The Sub-Saharan Africa agriculture involves diverse crops and livestock but productivity is particularly important for cereals and starchy roots, which provide two-thirds of the total energy intake for the population (three-quarters for the poor) (AGRA, 2013 citing Diao, Thurlow, Benin, & Fan, 2012). According to the Africa Human Development Report 2012 (United Nations Development Programme [UNDP], 2012), more than 75% of cereals and almost all root crops come from domestic agriculture and not imports (AGRA, 2013).

Many of the rural poor worldwide are smallholder farmers, and in most of South and South East Asia, and in much of sub-Saharan Africa, agriculture is dominated by smallholders (Jama and Pizarro, 2008 citing BIRTHAL et al. 2005 and Kydd, J. et al. 2002). In strategic terms, smallholder farming is generally viewed as indispensable to development as a whole (Jama and Pizarro, 2008). One common answer for the question why smallholders remain poor is that despite being relatively efficient users of resources, they remain poor because most poor countries provide them with only limited technical and economic opportunities to which they can respond and this is particularly the case in Africa, the only region in the world where per capita agricultural productivity has remained stagnant over the past 40 years (Jama and Pizarro, 2008 citing Sanchez, P.A. et al. 2005).

Until recently agricultural growth had resulted from an expansion of the area under crops or grazing rather than higher yields. However, demographic pressures have largely exhausted available land and in many areas, average farm sizes are falling, with typically areas of 2–5 ha dominating (Adekunle et al., 2012). At the same time, land quality has fallen. Data on nutrient balances over the past 30 years suggest that African soils have sustained annual net losses of nitrogen, phosphorus, and potassium on the order of 22, 2.5, and 15 kilograms per hectare respectively and this soil mining may contribute from one-third to as much as 80 percent of farm output in some locations (Haggblade, 2004). The lack of sufficient infrastructure, including rural access roads, irrigation, and land management capabilities, has resulted in the small amount of land available not being used at full potential. This problem is amplified by the common lack of capital and available funds to finance additional capital acquisition and insufficient financing continues to manifest in several ways, often equating to lack of dependable farm inputs such as high-yielding varieties of seeds, appropriate fertilizers, or cheap credit (AGRA, 2013 citing FAO, 2009).

Fortunately, African and donor governments have come to realize that they have marginalized agriculture for too long (Haggblade, 2004). Accordingly, through the consultative process of the New Partnership for Africa's

Development (NEPAD), the African heads of state have identified agriculture as a priority sector for stimulating economic growth and poverty reduction in Africa. Domestically, NEPAD aims to facilitate policies, strategies, and partnerships that will enhance the performance of agriculture in Africa. Internationally, it will continue to lobby for a more level playing field for African smallholders in international markets while promoting sub-regional cooperation and market development. Only sustained high-level political support will result in the policy incentives and long-term financial support to agricultural institutions that will, together, prove necessary for accelerating Africa's agricultural growth (Haggblade, 2004).

Some exciting efforts of African farmers and researchers in the past decade or so have significantly raised agricultural productivity in certain countries and for certain products (Haggblade, 2004). Notably, Ethiopia has more than doubled its domestic grain production (from 8 million metric tons in 2000 to 15.6 million metric tons in 2010) and is now Sub-Saharan Africa's second largest grain producer behind Nigeria (AGRA, 2013 citing USDA, 2012). Today, after widespread adoption by both commercial farmers and small holders, farmers now plant 58 percent of all maize area in East and Southern Africa to new high-yielding varieties, which on average out yield traditional varieties by 40–50 percent even without fertilizer (Haggblade, 2004). Despite the obvious challenges facing Sub-Saharan African countries with respect to agricultural productivity, recent successes recorded in Kenya, Malawi, Zambia, Uganda, Tanzania, Ethiopia, Mali, Burkina Faso, among other countries, have shown it is possible to achieve sustained agricultural growth in Sub-Saharan Africa (AGRA, 2013)

Given that Africa must grow faster than the rest of the world just to keep up with its increasing population, it remains true that the many individual successes achieved over the past half century have simply not been sufficient in number or scale (Haggblade, 2004). Due to the wide variety of local contexts in the African continent, a pluriform approach that specifically addresses the diversity is likely to work more effectively in increasing agricultural performance (Bindraban et al., 2009). Yield gap for most crops could be reduced by appropriate use of improved crop varieties; recommended application levels of appropriate fertilizers; and adequate management of nutrients, water, pests, and diseases (AGRA, 2013). Even if, in rare circumstances, smallholder farmers access irrigation, financing, technology, and adequate inputs, the lack of market access often lead to production failures. Market access problems persist in many areas, often resulting in many farmers not being able to sell their produce and hence resorting to subsistence production for their livelihoods (AGRA, 2013).

Though inadequate in scale and scope to outrun Africa's daunting demographics, these successes offer potentially important lessons for replicating and scaling up successful efforts more frequently in the future (Haggblade, 2004). Accordingly, drawing lessons from past success requires identifying a range of successful and less successful episodes and then studying and comparing them. With a wider range of institutional options now available, more evaluation is needed of what works well in what contexts (World Bank, 2007). In response to this need, the objective of this study is to identify the impact of adoption of improved maize technology package (including improved maize varieties, fertilizer of any kind as well as row planting) on maize yield of Ethiopia at national level.

## **2. Materials and Methods**

### *2.1 Analytical Framework for Evaluation*

The IFAD impact evaluation guidelines define impact as the “the attainment of development goals of the project or program, or rather the contributions to their attainment.” The ADB guidelines state the same point as follows: “project impact evaluation establishes whether the intervention had a welfare effect on individuals, households, and communities, and whether this effect can be attributed to the concerned intervention”. Assessing the impact of any intervention requires making an inference about the outcomes that would have been observed for program participants had they not participated (Smith and Todd, 2001). The evaluation problem can be regarded as a missing-data problem since, at a moment in time, each person is either in the program under consideration or not, but not both (Blundell and Dias, 2000). Accordingly, if we could observe the outcome variable for those in the program had they not participated, there would be no evaluation problem. Thus constructing the counterfactual is the central issue that evaluation methods address (Blundell and Dias, 2000).

Each of the evaluation methods in empirical economics that fall into five broad and related categories provides an alternative approach to constructing the counterfactual (Blundell and Dias, 2000). The methods utilized by researchers to circumvent this missing data problem are classified into two groups: selection on observables estimators and selection on unobservable estimators (Millimet and Tchernis, 2009). According to them, the distinction lies in whether a method consistently estimates the causal effect of the treatment in the presence of unobservable attributes of subjects that are correlated with both treatment assignment and the outcome of interest conditional on the set of observable variables.

Assuming a lack of such un-observables in which treatment assignment is said to be independent of potential outcomes conditional on the set of covariates X, one approach called the matching method aims to select sufficient observable factors that any two individuals with the same values of these factors will display no systematic differences in their reactions to the policy reform (Blundell and Dias, 2000; Millimet and Tchernis, 2009).

Consequently, if each individual undergoing the reform can be matched with an individual with the same matching variables who has not undergone the reform, the impact of the reform on individuals of that type can be measured (Blundell and Dias, 2000). To solve the dimensionality problem that is likely to arise if  $X$  is a lengthy vector, Rosenbaum and Rubin (1983) propose using the propensity score,  $P(X_i) = \Pr(T_i = 1|X_i)$ , instead of  $X$  as the conditioning variable (Millimet and Tchernis, 2009). Accordingly, however, if the conditional independence assumption (CIA) fails to hold, then consistent estimation of the causal effect requires a selection on unobservables estimation technique.

In fact, in the case of self-selection, it is usually reasonable to think that unobserved variables (like ability, intelligence, motivation, risk aversion) may critically determine the participation model (Heinrich et al., 2010). Accordingly, under the assumption that unobserved variables are time-invariant (that is, their value does not change with time), the effect can be cancelled out by taking the difference in outcomes before and after the program. This method is often labelled 'difference-in-differences' since it is usually implemented by comparing the difference in average behavior before and after the reform for the eligible group with the before and after contrast for the comparison group (Blundell and Dias, 2000). The simplest setting is one where outcomes are observed for units observed in one of two groups, in one of two time periods and only units in one of the two groups, in the second time period, are exposed to a treatment (Imbens and Wooldridge, 2009). Accordingly, there are no units exposed to the treatment in the first period, and units from the control group are never observed to be exposed to the treatment. This double differencing removes biases in second period comparisons between the treatment and control group that could be the result from permanent differences between those groups, as well as biases from comparisons over time in the treatment group that could be the result of time trends unrelated to the treatment (Imbens and Wooldridge, 2009). Unlike propensity score matching (PSM) alone, the difference-in-differences (DiD) estimator allows for unobserved heterogeneity that may lead to selection bias (Khandker et al., 2010). Accordingly, however, it assumes that this unobserved heterogeneity is time invariant. If time-varying unobservables are found to impact individual performance differences, then selection bias is not fully eliminated by differencing (Grilli L.). Even though DiD is unbiased only if the potential source of selection bias is additive and time invariant, one can conceive of several cases where unobserved characteristics of a population may indeed change over time—stemming, for example, from changes in preferences or norms over a longer time series (Khandker et al., 2010). A second drawback occurs if macro-level effects have a differential impact on treated and non-treated groups as one underlying assumption of the estimator is that treated and non-treated groups react similarly to shocks over time. This is true when the two groups differ for certain characteristics such that they react differently to common macro-level shocks (Grilli L.).

Even though all evaluation methods have risks for bias, the risk can sometimes be reduced by using a combination of methods since we can often offset the limitations of a single method and thus increase the robustness of the estimated counterfactual by combining methods (Gertler P.J. et al., 2011). In this regard, propensity score matching (PSM) can be combined with difference-in-differences (DiD) methods to better match control and project units on preprogram characteristics provided that rich data on control and treatment areas exist (Khandker et al., 2010). Although simple PSM cannot account for unobserved characteristics that might explain why a group chooses to enroll in a program and that might also affect outcomes, matching combined with difference-in-differences known as matched difference-in-differences or the Conditional Differences in Differences (CDiD) approach at least takes care of any unobserved characteristics that are constant across time between the two groups (Gertler P.J. et al., 2011). On the other hand, application of the CDiD estimator would help to overcome the second drawback of the DiD estimator mentioned above (Grilli L.). As to Blundell and Dias 2000, a non-parametric propensity score approach to matching that combines this method with difference-in-differences has the potential to improve the quality of non-experimental evaluation results significantly. Moreover, several design replications in labor economics have argued that pre-processing the data with matching, followed by a difference-in-difference estimator, performs better than a cross-sectional matching approach (Ferraro and Miranda, 2017 citing Heckman et al. 1997; Heckman, Ichimura, and Todd 1998; Smith and Todd 2005).

## 2.2 Data and Variables

The study used a balanced panel data of maize producers obtained from the second wave of the Ethiopia Socioeconomic Survey (ESS) 2013-2014 and the third wave of the Ethiopia Socioeconomic Survey (ESS) 2015-2016. The Ethiopian Socioeconomic Survey (ESS) is a collaborative long-term project between the Central Statistics Agency of Ethiopia (CSA) and the World Bank Living Standards Measurement Study-Integrated Surveys on Agriculture (LSMS-ISA) team to collect panel data. The project responds to the data needs of the country, given the dependence of a high percentage of households in agriculture activities in the country. The ESS collects information on household agricultural activities along with other information on the households like human capital, other economic activities, access to services and resources. The ability to follow the same households over time makes the ESS a new and powerful tool for studying and understanding the role of agriculture in household welfare over time as it allows analyses of how households add to their human and physical capital, how education affects

earnings, and the role of government policies and programs on poverty, inter alia. The ESS is the first panel survey to be carried out by the CSA that links a multi-topic household questionnaire with detailed data on agriculture. ESS uses a nationally representative sample of over 5,000 households living in rural and urban areas. The urban areas include both small and large towns. The sample is a two-stage probability sample. The first stage of sampling entailed selecting primary sampling units, which are a sample of the CSA enumeration areas (EAs). The second stage of sampling was the selection of households to be interviewed in each EA. A total of 433 EAs were selected based on probability proportional to size of the total EAs in each region out of which 290 were rural, 43 were small town EAs from ESS1, and 100 were EAs from major urban areas. In order to ensure sufficient sample size in the most populous regions (Amhara, Oromiya, SNNP, and Tigray) and Addis Ababa, quotas were set for the number of EAs in each region. The sample is not representative for each of the small regions including Afar, Benshangul Gumuz, Dire Dawa, Gambella, Harari, and Somalie regions. However, estimates can be produced for a combination of all smaller regions as one "other region" category.

During wave 3, 1255 households were re-interviewed yielding a response rate of 85 percent. Attrition in urban areas is 15% due to consent refusal and inability to trace the whereabouts of sample households.

Yield stands for the yield of maize per unit of land cropped measured in quintals per hectare.

LnYield stands for the natural logarithmic transformation of Yield.

HHAGE stands for the age of a household head in years.

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

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 in any language / and 0 if otherwise.

HHRELIGION is a dummy variable indicating the main religion of a household head.

FAMILY\_SIZE stands for size of a household.

CREDIT is a dummy variable indicating household's access to credit where CREDIT = 1 if anyone in the household has borrowed greater than 150 birr from someone outside the household or from an institution for business or farming purposes over the past 12 months and 0 if otherwise.

LANDHOLDING\_SIZE stands for size of the land holding of a household measured in meter squared.

OVERALLPLOTOWN is a dummy variable indicating household's plot ownership where OVERALLPLOTOWN = 1 if the household has some plot under its ownership (acquired through inheritance or local leaders' grant) and 0 if otherwise.

AVERPLOTSLOPE stands for the average plot slope of a household' overall plot measured in percent.

OVERALLFERTILEPLOT is a dummy variable indicating household's overall plot soil quality where OVERALLFERTILEPLOT = 1 if the household has some plot with fair or good soil quality and 0 if otherwise.

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

DSTMAJROAD stands for distance to the nearest major road from residence measured in kilometer.

DSTNEARPOPCENTER stands for distance to the nearest population center with more than 20,000 people from residence measured in kilometer.

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

HHTLU stands for the total livestock units currently owned and kept by a household.

EXCONTACT is a dummy variable indicating whether a household had participated in the extension program where EXCONTACT = 1 if the household had participated in the extension program and 0 if otherwise.

NONAGRIBUSIN is a dummy variable indicating whether a household owned a non-agriculture business or provided a non-agricultural service from home over the past 12 months where NONAGRIBUSIN = 1 if the household has owned a non-agriculture business or provided a non-agricultural service from home over the past 12 months and 0 if otherwise.

COMIRRIGSCH is a dummy variable indicating presence of an irrigation scheme in the community in which a household reside where COMIRRIGSCH = 1 if the community in which a household reside has an irrigation scheme and 0 if otherwise.

AMTOFRAIN is a dummy variable indicating the amount of rain received in the last season.

### **3. Results and Discussions**

#### *3.1 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 table 1.

#### *3.2 Propensity Scores Estimation using Probit Model*

Propensity scores for late adopters and non-adopters of fertilizer 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 fertilizer adoption were used in estimating the propensity scores. The check for 'overlap condition' across the

treatment and control groups was done and the result as indicated on figure 1 showed that the overlap condition is satisfied as there is substantial overlap in the distribution of the propensity scores of both late adopters and non-adopters. Each observation's propensity scores are calculated using a probit model. The propensity score for late adopters ranges between 0.0143852 and 0.7082498 while it ranges between 0.0090033 and 0.6258883 for non-adopters. And the region of common support for the distribution of estimated propensity scores of late adopters and non-adopters ranges between 0.0143852 and 0.70824977. When matching techniques are employed, observations whose propensity score lies outside this range were discarded.

### *3.3 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  $R^2$ , decreasing mean standardized bias, the insignificant p-values of the likelihood ratio test and satisfied interval value of Rubin's R (ratio of treated to (matched) non-treated variances of the propensity score index) after matching.

### *3.4 Average Treatment Effect on the Treated*

The ATT, calculated with the differences in differences (DiD) estimator and different matching algorithms (nearest neighbor matching one and five (NN=1 and NN=5) as well as Epanechnikov kernel matching with two band widths (BW=0.03 and BW=0.06), i.e.), are shown in table 3. Adoption of improved variety with fertilizer and row planting has some positive effects. During the period of investigation it increased yield growth of maize by 54-64%. These results are quite different from the simple comparison of yield growth in table 1, confirming that there is significant negative selection bias. That means, farmers with lower than average yield growth are more likely to adopt improved variety with fertilizer and row planting. Hence, a simple comparison between late adopters and non-adopters underestimates its treatment effect. This selection bias is controlled for by the PSM and DiD methodology. Moreover, all of the estimates in table 3 are significant, underlining the robustness of the results.

## **4. Conclusion and Recommendation**

This study is undertaken to identify the impact of adoption of improved maize technology package (including improved maize varieties, fertilizer of any kind as well as row planting) on maize yield growth of Ethiopia at national level. Unlike most previous impact studies of different improved agricultural technologies and practices, it used panel data covering two time periods. This allowed propensity score matching (PSM) to be combined with a difference-in-differences (DiD) estimator to better match control and project units on preprogram observable characteristics and to control for certain types of unobserved variables which can be assumed to remain fixed over a shorter time series. The study also employed and compared various matching algorithms to ensure robustness of the impact estimates. The estimation results show that adoption of improved maize technology package (including improved maize varieties, fertilizer of any kind as well as row planting) had positive and significant impact on maize yield growth of Ethiopia at national level. Therefore, this study recommends to widely scale-up the efficient use of improved maize varieties in combination with other complementary inputs and agronomic practices-appropriate and affordable fertilizer and labor-saving row planting techniques-to all maize producing farm households which obviously calls for embracing the enormous diversity of the production systems as well as a well-coordinated, effective as well as efficient effort of all of the relevant stakeholders of the agricultural sector of the country including farmers supported with a major recommitment to effective overall management of so many facets of the economic environment.

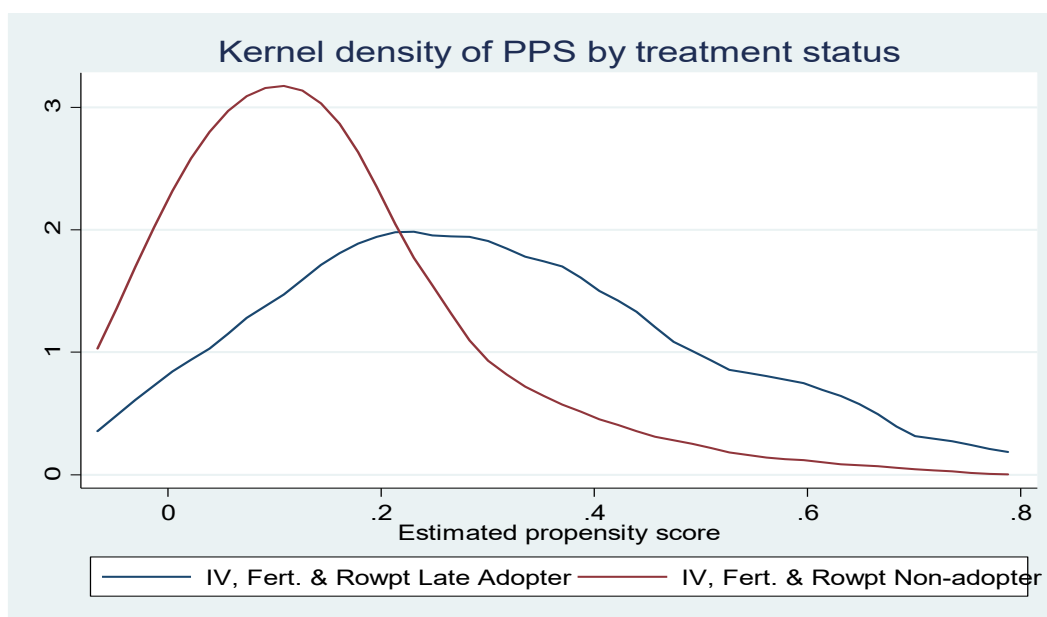


Figure 1: Distribution of propensity scores of late adopters and non-adopters

Table 1: Descriptive statistics of important variables used in the probit model-Propensity score matching (2013-2014)

Variables	Unit	Late Adopters of Improved Technology Package Mean(se)	Non-Adopters of Improved Technology Package Mean(se)	Aggregate Mean(se)	t-stat.
<b>Outcome variable</b>					
Yield	#	680.51(666.27)	40.38(14.57)	135.61(99.80)	-2.30**
LnYield	%	2.59(0.26)	2.66(0.0742)	2.65(0.0736)	0.36
<b>Variables that affect probability of adoption</b>					
HHAGE	#	44.11(2.14)	45.54(1)	45.34(0.91)	0.54
HHSEX (Male=1)	1=Yes	1.167(0.063)	1.147(0.024)	1.149(0.022)	-0.31
HHEDU (Read & write=1)	1=yes	1.44(0.0840)	1.68(0.0313)	1.65(0.0297)	2.80***
HHRELIGION	1=Orthodox	0.25(0.0732)	0.311(0.0309)	0.303(0.0285)	0.74
HHRELIGION	1=Protestant	0.389(0.082)	0.236(0.028)	0.257(0.027)	-1.96**
HHRELIGION	1=Muslim	0.28(0.076)	0.41(0.033)	0.39(0.030)	1.55*
FAMILY_SIZE	#	5.97(0.307)	5.66(0.162)	5.70(0.146)	-0.74
CREDIT	1=yes	0.111(0.053)	0.102(0.020)	0.103(0.019)	-0.16
LANDHOLDING_SIZE	Sq.m	21745.8(2456.3)	18959.9(1180.2)	19388.5(1067.8)	-0.94
OVERALLPLOT-OWN	1=yes	0.972(0.028)	0.92(0.018)	0.927(0.016)	-1.12
AVERPLOTSLO-PE	%	14.14(0.96)	12.69(0.71)	12.89(0.62)	-0.80
OVERALLFER-TILEPLOT	1=yes	0.857(0.060)	0.849(0.024)	0.85(0.022)	-0.13
DSTNEARMKT	km	70.1(7)	92.6(4.4)	86.5(3.9)	1.97**
DSTMAJROAD	km	16.16(1.97)	16.26(1.19)	16.25(1.06)	0.03
DSTNEARPOP-CENTER	km	43.6(4.4)	49.3(2.05)	48.5(1.9)	1.04
OXEN	#	1.09(0.198)	1.05(0.083)	1.06(0.077)	-0.14
HHTLU	#	2.85(0.31)	3.37(0.23)	3.29(0.198)	0.92

Variables	Unit	Late Adopters of Improved Technology Package Mean(se)	Non-Adopters of Improved Technology Package Mean(se)	Aggregate Mean(se)	t-stat.
EXCONTACT	1=yes	0.56(0.0840)	0.21(0.0272)	0.26(0.0271)	-4.58***
NONAGRIBUSIN	1=yes	1.97(0.0278)	1.89(0.0210)	1.9(0.0186)	-1.55*
COMIRRIGSCH	1=yes	1.333(0.0710)	1.464(0.0334)	1.45(0.0309)	1.47*
AMTOFRAIN	1=Too Much	0.417(0.083)	0.249(0.029)	0.272(0.028)	-2.11**
AMTOFRAIN	1=Right Amount	0.583(0.083)	0.551(0.033)	0.556(0.031)	-0.36
AMTOFRAIN	1=Too little	0(0)	0.196(0.027)	0.169(0.023)	2.95***

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

Source: Own computation, 2020

**Table 2: Propensity score matching quality test**

Sample	Ps R2	LR chi2	p>chi2	Meanbias	Medbias	R	%Var
Unmatched	0.156	30.35	0.000	42.8	33.3	1.43*	25
Matched	0.150	14.95	0.060	20.6	20.1	1.20	0

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

**Table 3: Average treatment effect on the treated (ATT) of fertilizer (2013-2014 and 2015-2016)**

Outcome Variable	Matching Algorithm	ATT (Std. Err.)
LnYield	Nearest Neighbor (NN=1)	0.635**(0.379)
	Nearest Neighbor (NN=5)	0.535*(0.341)
	Kernel (BW=0.03)	0.620*(0.390)
	Kernel (BW=0.06)	0.553*(0.374)

\*\*, \* indicate significance at 5 percent and 10 percent level respectively and bootstrapped standard errors are based on 100 replications.

Source: Own computation, 2020

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