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Impact of Row Planting on Maize Yield Growth in Ethiopia: The Implementation of the Difference-in-Differences Matching Estimator

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Abstract

This study examines the national level impact of adoption of row planting on maize yield growth in Ethiopia. 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 adoption of row planting doesn't have a significant impact on maize yield growth at national level. Therefore, this study does not recommend to widely scale-up adoption of mere row planting to all maize producing farm households.

Keywords: Impact, Maize, Row Planting, Ethiopia

1. Introduction

In the agriculture-based countries which include most of Sub-Saharan Africa like Ethiopia, agriculture is a major source of growth, accounting for 32 percent of GDP growth on average and most (70 percent) of the poor are in rural areas (World Bank, 2007). Crop production, on the other hand, is the dominant sub-sector within agriculture, accounting for more than 60% of the agricultural GDP and five cereals are cultivated on a wide scale: teff (an indigenous crop widely grown only in Ethiopia and Eritrea), wheat, maize, sorghum, and barley (Bekabil, 2018 citing Mulat et al., 2004; Dorosh and Rashid, 2012). 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. Abate et al. 2015 indicated that maize, teff (Eragrostis tef), sorghum, wheat, and barley among cereals and enset (Ensete ventricosum) (″false banana″) among ″roots and tubers″ provide the main calorie requirements in the Ethiopian diet. Therefore, a closer look at what is happening in cereal production has an important welfare and policy implication in Ethiopia (Abegaz, 2011). With increased production driving market prices down, maize became more affordable (e.g., relative to other staples such as teff and wheat) to rural and urban consumers (Abate et al., 2015). They added that it is now increasingly used both separately as well as in mixed flour with other more expensive cereals in traditional Ethiopian diets. Maize for industrial use has also supported growing demand according to them. Accordingly, though very little maize is currently used as feed, this too is changing in order to support a rapidly growing urbanization and poultry industry. Moreover, if production can be significantly expanded, the potential for maize export to all the neighboring countries including Kenya is very high although the national demand is expected to continue to grow in the coming years (Abate et al., 2015). Maize, according to Dorosh and Rashid 2012, is the second most widely cultivated cereal in Ethiopia in terms of area but is produced by more farms than any other crop. It accounts for the largest share of production by volume at 18.8 percent and appears to be increasing throughout Ethiopia largely because of the increasing demand driven by population growth and competitiveness of the crop (Abate et al., 2015 citing Rosegrant et al., 2001; Dorosh and Rashid, 2012).

In Ethiopia, agricultural production is dominated by smallholder households which produce more than 90% of agricultural output and cultivate more than 90% of the total cropped land (Bekabil, 2018). Smallholder production is dominated by five major cereal crops—teff, maize, wheat, sorghum, and barley—accounting for almost three quarters of the total cultivated area and about 68 percent of total production (Dorosh and Rashid, 2012). Improving the productivity, profitability, and sustainability of smallholder farming is the main pathway out of poverty in using agriculture for development. In this regard, a broad array of policy instruments, many of which apply differently to commercial smallholders and to those in subsistence farming, can be used to achieve the following: improve price incentives and increase the quality and quantity of public investment; make product markets work better; improve access to financial services and reduce exposure to uninsured risks; enhance the performance of producer organizations; promote innovation through science and technology; make agriculture more sustainable and a provider of environmental services (World Bank, 2007).

The increase in food needs as well as the industrial demand for agricultural products require an increase in the agricultural production (Bor and Bayaner, 2009). Although a majority of production increases in the past occurred due to increases in the area cultivated, area and yield increases each accounted for about half of production growth in the 2000s and we thus see an initial start of increasing intensification (Bekabil, 2018; Dorosh and Rashid, 2012). Accordingly, with little suitable uncultivated land available for expansion of crop cultivation apart from pasture land, especially in the highlands, production gains in terms of yield increases are critical to meet agricultural growth goals. As stated by MoARD (2010), increasing productivity in smallholder agriculture is the Government's top priority (Bekabil, 2018). Over the past two decades, decision-makers in Ethiopia have pursued a range of policies and investments to boost agricultural production and productivity, particularly with respect to the food staple crops that are critical to reducing poverty in the country (Dorosh and Rashid, 2012). Accordingly, a central aim of this process has been to increase the availability of improved seed, chemical fertilizers, and extension services for small-scale, resource-poor farmers, particularly those cultivating food staple crops. Although there is some evidence to suggest that the process has led to improvements in both output and yields during this period, decision-makers still recognize that there is extensive room for improvement (Dorosh and Rashid, 2012).

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). Accordingly, national maize yields have doubled from about 1.50 MT/ha during the early 1990s to 3.23 MT/ha in 2013. On average, maize area and productivity increased by 4.0 and 6.3% per annum, respectively, during the 10 years between 2004 and 2013. Similarly, the annual rate of growth for production during the same period was 10.5% and it is interesting to see that the increases in maize production in Ethiopia resulted more from increases in productivity rather than area expansion (Abate et al., 2015). 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.

Appropriate evaluation of the impact of those efforts of the past few decades in general and of the past recent years in particular is believed to be useful in order to create a more fertile ground for the fast and better achievement of the aforementioned goal. However, studies assessing the contribution of improved inputs and crop management practices for the productivity growth and other outcomes of interest of such important and widely cultivated cereals like maize carried out in Ethiopia in the past were not only few but also restricted to piece meal or location specific approach. As a result, the conclusions drawn from such studies that didn't use a nationally or regionally representative data would have low probability of influencing national and regional policies. Thus, the objective of this study is to identify the impact of use row planting on maize yield growth in Ethiopia.

2. Materials and Methods

2.1 Analytical Framework for Evaluation

The basic impact evaluation question essentially constitutes a causal inference problem and assessing the impact of a treatment or an intervention like a program on a series of outcomes is equivalent to assessing the causal effect of the program on those outcomes (Gertler P.J. et al., 2011). Following the literature, according to Lechner 2010, the event for which we want to estimate the causal effect is called the treatment and the outcome denotes the variable that will be used to measure the effect of the treatment. The answer to the basic impact evaluation question—*what is the impact or causal effect of a program P on an outcome of interest Y?*—is given by the basic impact evaluation formula: $\alpha = (Y \mid P = 1) - (Y \mid P = 0)$ (Gertler P.J. et al., 2011). Accordingly, we can think of the impact (α) of a program as the difference in outcomes (Y) for the same individual with and without participation in a program. Ideally, one would like to compare how the same household or individual would have fared with and without an intervention or "treatment." But one cannot do so because at a given point in time a household or an individual cannot have two simultaneous existences—a household or an individual cannot be in the treated and the control groups at the same time. So the challenge of an impact assessment is to create a convincing and reasonable comparison group for beneficiaries in light of this missing data (Khandker et al., 2010).

Although cause-and-effect questions are common, it is not a straightforward matter to establish that a relationship is causal (Gertler P.J. et al., 2011). As to Khandker et al. 2010, a program or policy intervention seeks to alter changes in the well-being of intended beneficiaries and ex-post, one observes outcomes of this intervention on intended beneficiaries, such as employment or expenditure. Does this change relate directly to the intervention? Has this intervention caused expenditure or employment to grow? Not necessarily. In fact, with only a point observation after treatment, it is impossible to reach a conclusion about the impact. According to them, one can say at best whether the objective of the intervention was met. But the result after the intervention cannot be attributed to the program itself. To establish causality between a program and an outcome, we use impact evaluation methods to rule out the possibility that any factors other than the program of interest explain the observed impact (Gertler P.J. et al., 2011). Impact evaluation provides a framework sufficient to understand whether the beneficiaries are truly benefiting from the program—and not from other factors (Khandker et al., 2010).

In practice, a key goal of an impact evaluation is to identify a group of program participants (the treatment group) and a group of nonparticipants (the comparison group) that are statistically identical in the absence of the program (Gertler P.J. et al., 2011). Accordingly, if the two groups are identical, excepting only that one group participates in the program and the other does not, then we can be sure that any difference in outcomes must be due to the program. The key challenge, then, is to identify a valid comparison group that has the same characteristics as the treatment group (Gertler P.J. et al., 2011). How about a comparison between treated and non-treated groups when both are eligible to be treated? How about a comparison of outcomes of treated groups before and after they are treated? These potential comparison groups can be "counterfeit" counterfactuals (Khandker et al., 2010). Specifically, the treatment and comparison groups must be the same in at least three ways: First, the treatment group and the comparison group must be identical in the absence of the program. Although it is not necessary that every unit in the treatment group be identical to every unit in the comparison group, on average the characteristics of treatment and comparison groups should be the same. Second, the treatment and comparison groups should react to the program in the same way. Third, the treatment and comparison groups cannot be differentially exposed to other interventions during the evaluation period (Gertler P.J. et al., 2011).

Even though the problem of selection bias can be reduced through different statistical methods, propensity score matching (PSM) is a popular method which can control for bias due to observed differences between treatment and control groups (Kikulwe et al. 2010 citing Rosenbaum and Rubin 1983; Mendola 2007; Becerril and Abdulai 2010). However, it is important to recognize that, unlike randomized trials, PSM does not necessarily balance the treatment and comparison groups on the basis of unobserved variables (Crown W.H.). Accordingly, parametric instrumental variables models attempt to address this issue by finding variables that are correlated with treatment selection but uncorrelated with the outcome variable. Although the method of instrumental variables is extremely appealing conceptually, it turns out to be very difficult to find such variables in practice and as a result, the use of instrumental variables can sometimes introduce more bias than it corrects (Crown W.H.).

Difference-in-Difference (DiD) is an attractive empirical strategy in cases when controlling for confounding variables is not possible and attractive instruments are not available and at the same time pre-treatment information is available though (Lechner, 2010). According to him, the basic idea of this identification strategy is that if the two treatment groups (the group who already received the treatment or post-treatment treated and the treated group prior to their treatment or pre-treatment treated) and the two non-treated groups (the non-treated group in the period before the treatment occurs to the treated or pre-treatment non-treated and the non-treated group in the current period or post-treatment non-treated) are subject to the same time trends, and if the treatment has no effect in the pre-treatment period, then we use the mean changes of the outcome variables for the non-treated over time and add this to the mean level of the outcome variable for the treated prior to treatment to obtain the mean outcome the treated would have experienced if they had not been subject to the treatment. Unlike PSM alone, the 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, so the bias cancels out through differencing. If a researcher finds that time-varying un-observables impact individual performance differences, then selection bias is not fully eliminated by differencing (Grilli L.). 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 off set 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, an extension of the DiD estimator that combines the advantages of PSM with the simplicity of DiD methods is introduced (Grilli L. citing Abadie and Imbens, 2006; Blundell and Dias, 2009). 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.). Obviously, it remains impossible to remove eventual relevant unobserved time-varying factors (Grilli L.).

The Conditional Differences in Differences (CDiD) approach is a three step procedure:

• First, to perform matching based on observed baseline characteristics which could help match treatment units with one or more observationally similar control units.

• Second, to exploit the longitudinal nature of data by conducting a DiD on the units that remain in the common support.

• Finally, average out those double differences across matched subgroups (Gertler P.J. et al., 2011; Grilli L.; Khandker et al., 2010).

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 row planting 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 row planting 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 0.0475575 and 0.7128858 while it ranges between 0.0068651 and 0.4609367 for non-adopters. And the region of common support for the distribution of estimated propensity scores of late adopters and non-adopters ranges between 0.04755755 and 0.71288576. 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 and satisfied interval value of Rubin's R (ratio of treated to (matched) non-treated variances of the propensity score index) after matching.

3.3 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 row planting does not have a significant effect on yield growth of maize. During the period of investigation it increased, however, yield growth of maize by 11-35% though not significant. 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 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 insignificant, underlining the robustness of the results.

4. Conclusion and Recommendation

This study is undertaken to identify the impact of adoption of row planting on maize yield growth in Ethiopia. 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 row planting does not have a significant impact on maize yield growth at national level. Therefore, this study does not recommend to widely scale-up adoption of mere row planting to all maize producing farm households.

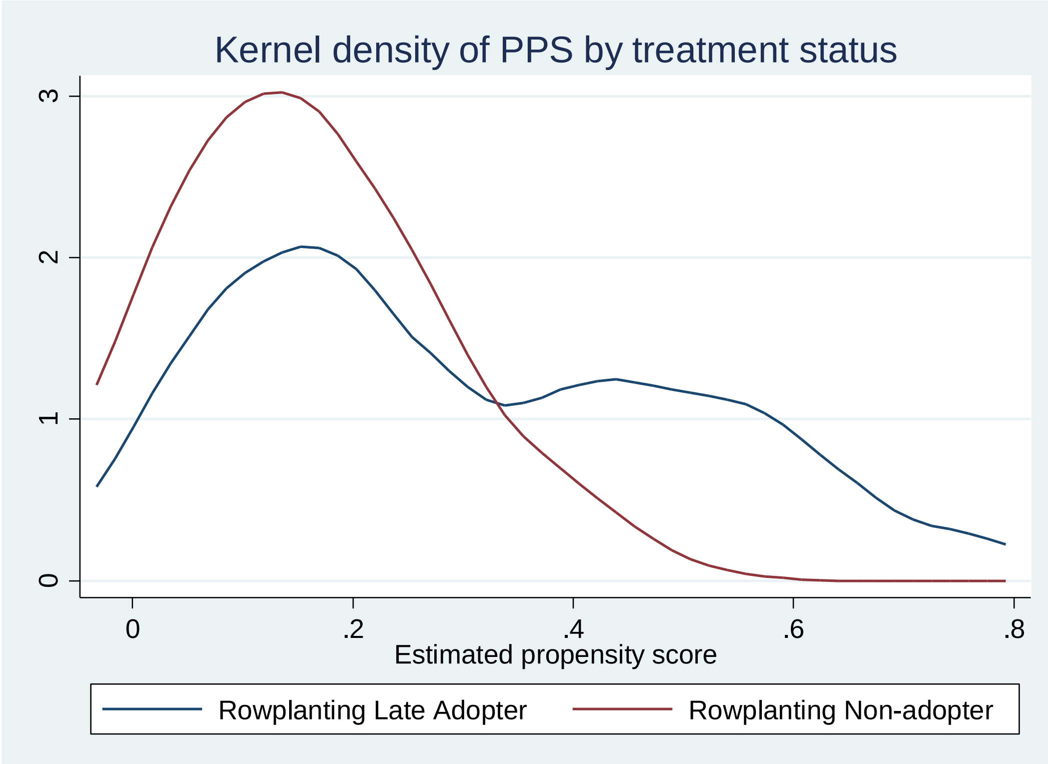

Figure 1: Distribution of propensity scores of late adopters and non-adopters

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

Variables	Unit	Late Adopters of Row Planting Mean(se)	Non-Adopters of Row Planting Mean(se)	Aggregate Mean(se)	t-stat.
Outcome variable					
Yield	#	30.27(9.62)	40.67(14.36)	38.82(11.94)	0.33
LnYield	%	2.638(0.179)	2.696(0.073)	2.686(0.068)	0.329
Variables that affect probability of adoption					
HHAGE	#	43.70(1.467)	45.62(1.006)	45.30(0.873)	0.823
HHSEX (Male=1)	1=Yes	1.196(0.059)	1.158(0.024)	1.164(0.022)	-0.629
HHEDU (Read & write=1)	1=yes	1.565(0.074)	1.677(0.031)	1.658(0.029)	1.457*
HHRELIGION	1=Or-thodox	0.261(0.0655)	0.311(0.0307)	0.303(0.0278)	0.679
HHRELIGION	1=Pro-testant	0.435(0.0739)	0.224(0.0277)	0.259(0.0265)	-3.019***
HHRELIGION	1=Mus-lem	0.261(0.0655)	0.417(0.0327)	0.391(0.0295)	1.983**
FAMILY_SIZE	#	6.02(0.415)	5.75(0.160)	5.79(0.150)	-0.683
CREDIT	1=yes	0.1739(0.05650)	0.1009(0.01999)	0.1131(0.01917)	-1.427
LANDHOLDING_SIZE	Sq.m	15257.95 (2269.1)	18707.17 (1137.2)	18064.36 (1019.2)	1.32*
OVERALLPLOTOWN	1=yes	1(0)	0.921(0.018)	0.934(0.015)	-1.978**
AVERPLOTSLOPE	%	9.834(1.143)	13.049(0.711)	12.509(0.626)	1.931**
OVERALLFERTILEPLOT	1=yes	0.911(0.043)	0.851(0.024)	0.861(0.021)	-1.065

Variables	Unit	Late Adopters of Row Planting Mean(se)	Non-Adopters of Row Planting Mean(se)	Aggregate Mean(se)	t-stat.
DSTNEARMKT	km	84.93(8.60)	91.10(4.34)	90.06(3.89)	0.592
DSTMAJROAD	km	14.99(2.75)	15.55(1.12)	15.45(1.04)	0.2009
DSTNEARPOP-CENTER	km	52.82(4.397)	48.26(1.984)	49.02(1.808)	-0.944
OXEN	#	0.85(0.164)	1.07(0.083)	1.03(0.075)	1.0905
HHTLU	#	3.64(0.565)	3.45(0.230)	3.48(0.214)	-0.343
EXCONTACT	1=yes	0.261(0.065)	0.232(0.028)	0.237(0.026)	-0.412
NONAGRIBUSIN	1=yes	1.91(0.042)	1.89(0.021)	1.89(0.019)	-0.455
COMIRRIGSCH	1=yes	1.30(0.069)	1.48(0.033)	1.45(0.030)	2.143**
AMTOFRAIN	1=Too Much	0.304(0.069)	0.263(0.029)	0.270(0.027)	-0.572
AMTOFRAIN	1=Right Amount	0.652(0.071)	0.539(0.033)	0.558(0.030)	-1.404
AMTOFRAIN	1=Too little	0.043(0.030)	0.193(0.026)	0.168(0.023)	2.494***

***, **, * indicate significance at 1 percent, 5 percent and 10 percent level respectively.
Source: Own computation, 2021

Table 2: Propensity score matching quality test

Sample	Ps R2	LR chi2	p>chi2	Meanbias	Medbias	R	%Var
Unmatched	0.132	31.71	0.000	39.2	38.4	1.54	0
Matched	0.038	4.80	0.441	9.9	9.3	1.32	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)	0.228(0.342)
	Nearest Neighbor (NN=5)	0.114(0.330)
	Kernel (BW=0.03)	0.354(0.301)
	Kernel (BW=0.06)	0.124(0.335)

Bootstrapped standard errors are based on 100 replications.
Source: Own computation, 2021

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