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Impact of Improved Wheat Varieties Adoption on Productivity: Disparity among Agroecological Zones of Ethiopia

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ABSTRACT

This study examines the agroecologic zonal disparity in the impact of adoption of improved wheat varieties 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. It is found that adoption of improved wheat varieties doesn't have homogeneous positive and significant impact on productivity growth in all of the agroecologic zones considered. Thus, the study recommends that the agricultural research and extension system of the country should further consider the various differences that exist among different agroecologic zones and other areas of the country so as to generate and disseminate suitable improved agricultural technologies and information to each areas.

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 (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 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. As a result, the issue has not been satisfactorily and comprehensively assessed at national, regional as well as agroecologic zonal level. Thus, the objective of this study is to identify the agroecologic zonal disparity in the impact of adoption of improved wheat varieties on wheat productivity per unit of land cropped among the four major administrative regions of Ethiopia which are also known to be the major wheat producing regions in the country.

Analytical Framework for Evaluation of Adoption of Wheat Variety Impact on Productivity

The correct evaluation of the impact of a treatment like adoption of a technology 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:

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

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- Oromia, Tigray, Amhara as well as South Nations, Nationalities and Peoples (SNNP). A multi-stage stratified sampling procedure was used to select "kebeles"/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 table 1. In SM3 (Tepid sub-moist mid highlands), H3 (Tepid humid mid highlands) and M4 (Cool moist mid highlands) agroecological zones, the productivity of improved wheat varieties adopters is significantly greater than that of non-adopters. Thus, it tentatively shows that there is significant difference in productivity level in these agroecological zones between those households that adopt improved wheat varieties and those that do not adopt improved wheat varieties. Some of the most important demographic determinants that influence adoption of a technology include gender, level of education and age. There exists a significant difference between adopters and non-adopters of wheat technology in terms of these demographic factors as depicted by the descriptive statistics. Those farmers who had contact with government extension workers are more likely to adopt improved wheat varieties than those that had not in four of the agroecological zones considered, namely M4 (Cool moist mid highlands), M3 (Tepid moist mid highlands), H4 (Cool humid mid highlands) and SH3 (Tepid sub-humid mid highlands). However, this variable had the unexpected negative and significant influence on the probability of adoption of improved wheat varieties in H3 (Tepid humid mid highlands). Age of a household head had the expected negative effect on the probability of adoption in four of the agroecological zones considered, namely M4 (Cool moist mid highlands), M3 (Tepid moist mid highlands), M2 (Warm moist lowlands) and SH3 (Tepid sub-humid mid highlands). This is in line with the fact that younger farmers have had more schooling than the older generation or have been exposed to new ideas and more risk takers according to Admassie and Ayele 2004. However, it also has the unexpected positive and significant effect on the probability of adoption of improved wheat varieties in SM2 (Warm sub-moist lowlands). Literate-headed household are more probable in adopting improved wheat varieties as expected in four of the agroecological zones considered-SM3 (Tepid sub-moist mid highlands), H4 (Cool humid mid highlands), M2 (Warm moist lowlands) and M4 (Cool moist mid highlands). 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, female-headed households were found to be more probable in adopting improved wheat varieties in three of the agroecological zones considered-H3 (Tepid humid mid highlands), M4 (Cool moist mid highlands) and SM3 (Tepid sub-moist mid highlands) which is a bit contradictory to the fact that such households are endowed with less resource and are less exposed to new information and ideas. They were found to be less probable in adopting improved wheat varieties as expected in SH3 (Tepid sub-humid mid highlands) only. While landholding size had positive and significant effect on the probability of adoption in only two of the agroecological zones considered, namely SM3 (Tepid sub-moist mid highlands) and SH2 (Warm sub-humid lowlands), it had the opposite effect in three of the agroecological zones considered, namely H3 (Tepid humid mid highlands), M3 (Tepid moist mid highlands) and SH3 (Tepid sub-humid mid highlands). Oxen ownership positively affected the probability of adoption of improved wheat varieties as expected in three of the agroecological zones considered, namely M3 (Tepid moist mid highlands), M2 (Warm moist lowlands) and H4 (Cool humid mid highlands). Households with relatively larger family size are more likely to adopt improved wheat varieties as expected in two of the agroecological zones considered, namely SM3 (Tepid sub-moist mid highlands) and M2 (Warm moist lowlands) because such households, on one hand, do not face labor shortage that may be needed to manage the increased output which resulted from technology adoption and, on the other hand, higher family size necessitates increased productivity to feed the family. However, the opposite holds true in M3 (Tepid moist mid highlands). Distance to the nearest main market had the expected inverse relation with the probability of adoption of improved wheat varieties in only one agroecological zone-SH3 (Tepid sub-humid mid highlands) while its relation with the probability of adoption is positive in two agroecological zones-M2 (Warm moist lowlands) and M3 (Tepid moist mid highlands). Finally, while the total number of traders known who could buy the produced grain had the expected positive and significant effect on the probability of adoption of improved wheat varieties in two agroecological zones-SH3 (Tepid sub-humid mid highlands) and H4 (Cool humid mid highlands), credit availability had the expected positive and significant effect on the same in only one agroecological zone-M4 (Cool moist mid highlands) because some technological recommendations implies a significant cash investment for farmers that needs to be acquired through either formal or informal sources as to Admassie and Ayele 2004.

Propensity Scores Estimation using Probit Model

The descriptive statistics of the key variables affecting technology adoption has shown a tentative impact of improved wheat varieties adoption on increasing productivity in some of the agroecological zones. Nevertheless, a mere comparison of productivity has no causal meaning since improved wheat varieties adoption is endogenous. And it is difficult to attribute the change to adoption of improved wheat varieties 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 varieties adoption on productivity in different wheat producing agroecological zones of Ethiopia. Propensity scores for 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 improved wheat varieties 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 for all the agroecological zones considered.

Each observation's propensity scores are calculated using a probit model. For the SM3 (Tepid sub-moist mid highlands) agroecological zone, the propensity score for adopters ranges between 0.646789 and 0.993057 while it ranges between 0.705018 and 0.9553841 for non-adopters and the region of common support for the distribution of estimated propensity scores of adopters and non-adopters ranges between 0.64678898 and 0.99305699. For the H3 (Tepid humid mid highlands) agroecological zone, the propensity score for adopters ranges between 0.6456033 and 0.864676 while it ranges between 0.6309877 and 0.8130688 for non-adopters and the region of common support for the distribution of estimated propensity scores of adopters and non-adopters ranges between 0.64560328 and 0.86467595. For the M4 (Cool moist mid highlands) agroecological zone, the propensity score for adopters ranges between 0.4422557 and 0.9830249 while it ranges between 0.4199786 and 0.9725372 for non-adopters and the region of common support for the distribution of estimated propensity scores of adopters and non-adopters ranges between 0.44225574 and 0.98302491. For the M3 (Tepid moist mid highlands) agroecological zone, the propensity score for adopters ranges between 0.3793544 and 0.9382406 while it ranges between 0.3834627 and 0.8850461 for non-adopters and the region of common support for the distribution of estimated propensity scores of adopters and non-adopters ranges between 0.3793544 and 0.93824059. For the SH2 (Warm sub-humid lowlands) agroecological zone, the propensity score for adopters ranges between 0.6288597 and 0.999464 while it ranges between 0.8452322 and 0.9395982 for non-adopters and the region of common support for the distribution of estimated propensity scores of adopters and non-adopters ranges between 0.62885974 and 0.99946404. For the SM2 (Warm sub-moist lowlands) agroecological zone, the propensity score for adopters ranges between 0.4062263 and 0.9554416 while it ranges between 0.1523165 and 0.8845029 for non-adopters and the region of common support for the distribution of estimated propensity scores of adopters and non-adopters ranges between 0.40622634 and 0.95544157. For the M2 (Warm moist lowlands) agroecological zone, the propensity score for adopters ranges between 0.407485 and 0.9969272 while it ranges between 0.243466 and 0.9582399 for non-adopters and the region of common support for the distribution of estimated propensity scores of adopters and non-adopters ranges between 0.40748504 and 0.99692722. For the H4 (Cool humid mid highlands) agroecological zone, the propensity score for adopters ranges between 0.7250804 and 0.9114118 while it ranges between 0.7311943 and 0.8987052 for non-adopters and the region of common support for the distribution of estimated propensity scores of adopters and non-adopters ranges between 0.7250804 and 0.91141184. For the SH3 (Tepid sub-humid mid highlands) agroecological zone, the propensity score for adopters ranges between 0.5086052 and 0.9999862 while it ranges between 0.6522311 and 0.9739358 for non-adopters and the region of common support for the distribution of estimated propensity scores of adopters and non-adopters ranges between 0.5086052 and 0.9999862.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)-1(i). 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 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 all regions except SH2 and SH3, decreasing mean standardized bias for all regions and satisfied interval value of Rubin's R (ratio of treated to (matched) non-treated variances of the propensity score index) after matching for all regions except M4, SH2 and SH3.

RESULTS

Different impact estimators were employed to get estimated treatment effect. Table 3 shows the average impact of improved wheat varieties adoption on productivity growth in those agroecological zones which are found in the four administrative regions of interest following nearest neighbor matching (NNM), Stratification Matching, Radius (Caliper) Matching and Kernel Matching (KM) techniques. Though improved wheat varieties adoption has a positive and significant impact on productivity growth in only three agroecological zones, namely SM3 (Tepid sub-moist mid highlands), H3 (Tepid humid mid highlands) and M4 (Cool moist mid highlands), its impact is not significant in the rest six agroecological zones-M3 (Tepid moist mid highlands), SH2 (Warm sub-humid lowlands), SM2 (Warm sub-moist lowlands), M2 (Warm moist lowlands), H4 (Cool humid mid highlands) and SH3 (Tepid sub-humid mid highlands). Furthermore, the impact is higher in SM3 (Tepid sub-moist mid highlands) and H3 (Tepid humid mid highlands), ranging from 31-52% and from 30-50% respectively, compared to that in M4 (Cool moist mid highlands), ranging from 25-45%.

CONCLUSION AND RECOMMENDATION

This study is undertaken to identify the agroecologic zonal disparity in the impact of adoption of improved wheat varieties on wheat productivity among different major wheat producing administrative regions of 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 varieties 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 varieties that were released and disseminated so far doesn't have the desired positive and significant impact on productivity growth in all of the different wheat producing agroecological zones of the country. Moreover, their impact greatly varies among the agroecologic zones. Therefore, this study recommends that the agricultural research and extension system of the country should be strengthened to further take into account the various differences among different agroecologic zones and other areas (like “woredas”/districts and “kebeles”/villages) in order to generate and scale-up improved wheat varieties as well as other appropriate improved agricultural technologies and information that suits to the specific conditions of all wheat producing farm households of the country.

Table 1: Descriptive statistics of important variables used in the probit model-Propensity Score Matching

Variables	Unit	Adopters Mean(se)				Non-adopters Mean(se)			
		SM3	H3	M4	M3	SM3	H3	M4	M3
Outcome variable									
Productivity	Kg/ha	1800.6 (65.77)	1568.3 (107.96)	1989.1 (97.36)	1371.3 (49.50)	1184.7 (109.83)	1106.0 (207.73)	1320.8 (97.08)	1260.2 (92.38)
LnProductivity	%	7.32 (0.0439)	7.23 (0.073)	7.39 (0.048)	7.06 (0.037)	6.91 (0.1034)	6.87 (0.155)	7.04 (0.083)	6.91 (0.072)
Variables that affect probability of adoption									
HHAGE	#	47.04 (0.88)	44.32 (2.01)	44.01 (0.80)	45.53 (0.74)	48.66 (2.19)	44.45 (3.39)	46.80 (2.03)	48.46 (1.46)
HHSEX (Male=1)	1=Yes	0.91 (0.019)	0.83 (0.052)	0.92 (0.0190)	0.91 (0.018)	0.97 (0.026)	1 (0)	0.98 (0.0185)	0.95 (0.023)
FAMILYSIZE	#	6.37 (0.131)	6.64 (0.27)	6.69 (0.168)	6.17 (0.13)	5.82 (0.266)	6.36 (0.41)	6.31 (0.289)	6.74 (0.22)
HHEDU (Read & write=1)	1=yes	0.68 (0.031)	0.66 (0.066)	0.65 (0.034)	0.57 (0.031)	0.53 (0.082)	0.73 (0.141)	0.50 (0.069)	0.51 (0.052)
CREDIT	1=yes	0.141 (0.023)	0.038 (0.026)	0.066 (0.0178)	0.0536 (0.014)	0.105 (0.050)	0 (0)	0.019 (0.0185)	0.0532 (0.023)
LANDHOLDING_SIZE	ha	1.40 (0.077)	1.31 (0.121)	1.59 (0.081)	1.54 (0.076)	1.09 (0.124)	1.77 (0.321)	1.43 (0.191)	1.84 (0.199)
DSTMNMKT	km	7.43 (0.32)	10.46 (1.11)	8.94 (0.44)	9.57 (0.39)	7.36 (0.67)	11.64 (1.50)	8.49 (0.68)	7.93 (0.45)
OXEN	#	2.12 (0.10)	2.132 (0.227)	2.11 (0.087)	2.16 (0.105)	1.95 (0.64)	2.091 (0.495)	2.24 (0.224)	1.85 (0.125)
TNOTRAREDS	#	3.89 (0.36)	3.26 (0.318)	4.42 (0.42)	4.37 (0.32)	3.24 (0.85)	4.18 (1.197)	4.98 (0.87)	3.96 (0.47)
EXCONTACT	1=yes	0.885 (0.021)	0.698 (0.064)	0.878 (0.0235)	0.83 (0.023)	0.868 (0.056)	1 (0)	0.741 (0.0602)	0.65 (0.049)

Source: Own computation, 2018

Table 1 - Cont.: Descriptive statistics of important variables used in the probit model-Propensity Score Matching

Variables	Unit	Adopters Mean(se)				Non-adopters Mean(se)			
		SH2	SM2	M2	H4	SH2	SM2	M2	H4
Outcome variable									
Productivity	Kg/ha	1130.1 (81.66)	1615.9 (157.32)	2054.7 (172.29)	2070.8 (97.98)	971.9 (28.13)	1562.2 (128.13)	1390.8 (208.57)	2394.5 (439.07)
LnProductivity	%	6.9324 (0.029)	7.339 (0.108)	7.35 (0.112)	7.52 (0.055)	6.8798 (0.074)	7.337 (0.085)	6.93 (0.259)	7.60 (0.266)
Variables that affect probability of adoption									
HHAGE	#	40.97 (2.29)	51.8 (2.494)	41.35 (1.27)	46.05 (1.43)	33 (1)	42.67 (4.470)	49.18 (3.55)	48.38 (5.06)
HHSEX (Male=1)	1=Yes	0.921 (0.044)	1 (0)	0.92 (0.033)	0.908 (0.031)	1 (0)	1 (0)	0.94 (0.059)	0.875 (0.125)
FAMILYSIZE	#	6.947 (0.397)	5 (0.596)	6.38 (0.261)	7.51 (0.29)	6.5 (0.5)	5.333 (0.422)	5.65 (0.445)	7.38 (0.63)
HHEDU (Read & write=1)	1=yes	0.84 (0.060)	0.5 (0.167)	0.55 (0.062)	0.784 (0.0441)	1 (0)	0.833 (0.167)	0.35 (0.119)	0.5 (0.189)
CREDIT	1=yes	0 (0)	0.2 (0.133)	0.045 (0.026)	0.034 (0.019)	0 (0)	0 (0)	0 (0)	0 (0)
LANDHOLDING_SIZE	ha	1.33 (0.118)	1.352 (0.192)	1.16 (0.117)	1.99 (0.122)	0.54 (0.21)	0.99 (0.151)	1.09 (0.136)	1.84 (0.50)
DSTMNMKT	km	10.59 (0.734)	6.35 (0.775)	7.87 (0.63)	11.40 (0.52)	13.50 (1.50)	5.50 (0.719)	6.09 (0.86)	9.25 (1.10)
OXEN	#	1.5 (0.17)	1.80 (0.389)	1.83 (0.168)	2.30 (0.160)	1.5 (0.50)	1.50 (0.342)	1.35 (0.270)	1.38 (0.324)
TNOTRAREDS	#	4.5 (1.311)	3 (1.193)	3.85 (0.63)	5.76 (0.460)	2 (1)	2.667 (1.476)	4.24 (0.93)	3.13 (1.008)
EXCONTACT	1=yes	0.84 (0.0599)	0.9 (0.1)	0.924 (0.033)	0.909 (0.0308)	1 (0)	1 (0)	0.882 (0.081)	0.75 (0.1637)

Source: Own computation, 2018

Table 1 - Cont.: Descriptive statistics of important variables used in the probit model-Propensity Score Matching

Variables	Unit	Adopters Mean(se)		Non-adopters Mean(se)	
		SH3	SM4	SH3	SM4
Outcome variable					
Productivity	Kg/ha	1686.5 (60.23)	1669.3 (114.90)	1327.1 (122.32)	1509.3 (157.00)
LnProductivity	%	7.24 (0.039)	7.215 (0.066)	7.14 (0.111)	7.194 (0.121)
Variables that affect probability of adoption					
HHAGE	#	45.59 (0.70)	48.90 (1.32)	52.1 (3.29)	50.09 (2.69)
HHSEX (Male=1)	1=Yes	0.92 (0.016)	0.849 (0.035)	0.70 (0.15)	0.909 (0.063)
FAMILYSIZE	#	7.23 (0.14)	5.71 (0.179)	6.9 (0.98)	5.91 (0.436)
HHEDU (Read & write=1)	1=yes	0.69 (0.028)	0.519 (0.049)	0.5 (0.17)	0.545 (0.109)
CREDIT	1=yes	0.05 (0.013)	0.142 (0.034)	0 (0)	0.091 (0.063)
LANDHOLDING_SIZE	ha	1.71 (0.097)	1.20 (0.090)	2.55 (0.43)	1.24 (0.156)
DSTMNMKT	km	9.47 (0.37)	9.41 (0.72)	13.6 (2.9)	10.36 (1.14)
OXEN	#	2.28 (0.13)	1.75 (0.123)	2.5 (0.79)	2 (0.279)
TNOTRAREDS	#	4.95 (0.36)	3.76 (0.54)	2 (0.33)	3.91 (1.25)
EXCONTACT	1=yes	0.802 (0.024)	0.896 (0.0298)	0.6 (0.16)	0.909 (0.0627)

Source: Own computation, 2018

Table 1 - Cont.: Descriptive statistics of important variables used in the probit model-Propensity Score Matching

Variables	Unit	Aggregate Mean(se)				t-stat.			
		SM3	H3	M4	M3	SM3	H3	M4	M3
Outcome variable									
Productivity	Kg/ha	1712.3 (59.92)	1488.8 (98.12)	1844.7 (80.98)	1341.9 (43.86)	-3.69***	-1.81**	-3.47***	-1.12
LnProductivity	%	7.26 (0.0413)	7.17 (0.068)	7.31 (0.042)	7.02 (0.033)	-3.56***	-2.06**	-3.50***	-1.97**
Variables that affect probability of adoption									
HHAGE	#	47.27 (0.82)	44.34 (1.75)	44.61 (0.77)	46.30 (0.67)	0.697	0.029	1.50*	1.93**
HHSEX (Male=1)	1=Yes	0.92 (0.017)	0.86 (0.044)	0.94 (0.0155)	0.92 (0.014)	1.30*	1.48*	1.54*	1.08
FAMILYSIZE	#	6.29 (0.119)	6.59 (0.23)	6.61 (0.146)	6.32 (0.11)	-1.65*	-0.45	1.06	2.29**
HHEDU (Read & write=1)	1=yes	0.66 (0.029)	0.67 (0.059)	0.62 (0.031)	0.55 (0.026)	-1.89**	0.42	-1.99**	-0.94
CREDIT	1=yes	0.136 (0.021)	0.031 (0.022)	0.056 (0.015)	0.0535 (0.012)	-0.59	-0.65	-1.35*	-0.017
LANDHOLDING_ SIZE	ha	1.35 (0.069)	1.39 (0.115)	1.56 (0.075)	1.62 (0.077)	-1.57*	1.52*	-0.91	1.72**
DSTMNMKT	km	7.42 (0.29)	10.67 (0.95)	8.84 (0.37)	9.13 (0.31)	-0.09	0.46	-0.50	-2.33**
OXEN	#	2.09 (0.13)	2.125 (0.205)	2.14 (0.083)	2.08 (0.084)	-0.47	-0.075	0.66	-1.63*
TNOTRAREDS	#	3.8 (0.33)	3.42 (0.332)	4.54 (0.38)	4.26 (0.27)	-0.70	1.04	0.61	-0.68
EXCONTACT	1=yes	0.883 (0.020)	0.75 (0.055)	0.848 (0.0228)	0.78 (0.022)	-0.30	2.15**	-2.50***	-3.64***

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

Table 1 - Cont.: Descriptive statistics of important variables used in the probit model-Propensity Score Matching

Variables	Unit	Aggregate Mean(se)				t-stat.			
		SH2	SM2	M2	H4	SH2	SM2	M2	H4
Outcome variable									
Productivity	Kg/ha	1122.2 (77.73)	1595.8 (106.67)	1918.5 (146.02)	2097.8 (96.58)	-0.439	-0.24	-1.86**	0.93
LnProductivity	%	6.9298 (0.071)	7.338 (0.073)	7.26 (0.105)	7.53 (0.054)	-0.16	-0.016	1.66*	0.39
Variables that affect probability of adoption									
HHAGE	#	40.58 (2.19)	48.38 (2.476)	42.98 (1.29)	46.24 (1.37)	-0.79	-1.94**	2.55***	0.47
HHSEX (Male=1)	1=Yes	0.925 (0.042)	1 (0)	0.93 (0.029)	0.905 (0.030)	0.40		0.25	-0.30
FAMILYSIZE	#	6.925 (0.378)	5.125 (0.397)	6.23 (0.228)	7.50 (0.27)	-0.25	0.395	-1.30*	-0.14
HHEDU (Read & write=1)	1=yes	0.85 (0.057)	0.625 (0.125)	0.51 (0.055)	0.760 (0.0438)	0.597	1.323	-1.42*	-1.81**
CREDIT	1=yes	0 (0)	0.125 (0.085)	0.036 (0.021)	0.031 (0.018)		-1.146	-0.89	-0.53
LANDHOLDING_SIZE	ha	1.29 (0.116)	1.216 (0.137)	1.14 (0.097)	1.98 (0.119)	-1.51*	-1.309	-0.299	-0.35
DSTMNMKT	km	10.74 (0.706)	6.03 (0.549)	7.51 (0.54)	11.22 (0.49)	0.895	-0.739	-1.34*	-1.22
OXEN	#	1.5 (0.16)	1.69 (0.270)	1.73 (0.146)	2.22 (0.151)	0	-0.526	-1.34*	-1.70**
TNOTRAREDS	#	4.375 (1.248)	2.875 (0.898)	3.93 (0.53)	5.54 (0.435)	-0.43	-0.174	0.29	-1.69**
EXCONTACT	1=yes	0.85 (0.0572)	0.938 (0.0625)	0.916 (0.031)	0.896 (0.0313)	0.597	0.764	-0.55	-1.41*

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

Source: Own computation, 2018

Table 1 - Cont.: Descriptive statistics of important variables used in the probit model-Propensity Score Matching

Variables	Unit	Aggregate Mean(se)		t-stat.	
		SH3	SM4	SH3	SM4
Outcome variable					
Productivity	Kg/ha	1674.0 (58.41)	1641.8 (98.84)	-1.13	-0.61
LnProductivity	%	7.24 (0.038)	7.212 (0.058)	-0.48	-0.13
Variables that affect probability of adoption					
HHAGE	#	45.82 (0.69)	49.10 (1.18)	1.73**	0.38
HHSEX (Male=1)	1=Yes	0.92 (0.016)	0.859 (0.031)	2.54***	0.73
FAMILYSIZE	#	7.22 (0.14)	5.74 (0.166)	-0.44	0.46
HHEDU (Read & write=1)	1=yes	0.68 (0.028)	0.523 (0.044)	-1.25	0.23
CREDIT	1=yes	0.049 (0.013)	0.133 (0.030)	-0.73	-0.63
LANDHOLDING_SIZE	ha	1.74 (0.095)	1.21 (0.079)	1.62*	0.18
DSTMNMKT	km	9.61 (0.37)	9.57 (0.63)	2.05**	0.57
OXEN	#	2.285 (0.12)	1.80 (0.112)	0.33	0.82
TNOTRAREDS	#	4.84 (0.35)	3.79 (0.49)	-1.53*	0.11
EXCONTACT	1=yes	0.795 (0.024)	0.898 (0.0268)	-1.56*	0.18

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

Table 2: Propensity Score Matching Quality Test

Region	Sample	Ps R2	LR chi2	p>chi2	MeanBias	MedBias	R	%Var
SM3 (Tepid sub-moist mid highlands)	Unmatched	0.050	10.97	0.027	29.9	30.3	1.87	100
	Matched	0.004	2.40	0.662	4.4	2.2	1.97	50
H3 (Tepid humid mid highlands)	Unmatched	0.012	0.59	0.441	68.9	63.4	1.01	0
	Matched	0.003	0.24	0.624	3.9	0.0	1.12	0
M4 (Cool moist mid highlands)	Unmatched	0.064	16.71	0.005	27.5	27.4	0.87	100
	Matched	0.016	8.68	0.122	10.6	5.1	2.87*	0
M3 (Tepid moist mid highlands)	Unmatched	0.060	24.49	0.000	24.1	21.9	0.75	60
	Matched	0.025	17.92	0.006	13.9	14.2	0.92	60
SH2 (Warm sub-humid lowlands)	Unmatched	0.168	2.67	0.102	136.9	136.9	2.70*	100
	Matched	0.182	19.13	0.000	93.1	93.1	18.07*	100
SM2 (Warm sub-moist lowlands)	Unmatched	0.174	3.68	0.055	95.7	95.7	0.52	0
	Matched	0.017	0.47	0.491	24.1	24.1	1.03	0
M2 (Warm moist lowlands)	Unmatched	0.145	12.12	0.033	42.0	37.3	0.83	25
	Matched	0.044	7.97	0.158	27.1	27.2	0.73	25
H4 (Cool humid mid highlands)	Unmatched	0.141	7.77	0.100	56.6	57.0	0.52	0
	Matched	0.062	15.13	0.004	22.6	23.3	1.47	50
SH3 (Tepid sub-humid mid highlands)	Unmatched	0.183	15.91	0.014	59.7	58.2	1.34	100
	Matched	0.331	254.82	0.000	50.0	43.3	4.06*	75

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

Table 3: Average Treatment Effects estimation using different propensity score matching estimators

Agroecologic Zone	Outcome Variable	Matching Algorithm	Mean of Outcome Variable Based on Matched Observations		ATT	t-stat.
			Adopters	Non-adopters		
SM3 (Tepid sub-moist mid highlands)	LnProductivity	Nearest Neighbor Matching	7.32	7.01	0.314	1.980**
		Stratification Matching			0.435	3.807***
		Caliper Matching	7.36	6.84	0.523	3.148***
		Kernel Matching	7.32	6.88	0.441	4.179***
H3 (Tepid humid mid highlands)	LnProductivity	Nearest Neighbor Matching	7.24	6.94	0.304	1.374*
		Stratification Matching			0.328	.
		Caliper Matching	7.16	6.66	0.496	2.023**
		Kernel Matching	7.24	6.87	0.374	2.103**
M4 (Cool moist mid highlands)	LnProductivity	Nearest Neighbor Matching	7.39	7.09	0.300	2.668***
		Stratification Matching			0.250	2.357***
		Caliper Matching	7.49	7.04	0.447	3.318***
		Kernel Matching	7.39	7.13	0.256	2.313**
M3 (Tepid moist mid highlands)	LnProductivity	Nearest Neighbor Matching	7.06	6.86	0.197	1.697**
		Stratification Matching			0.072	.
		Caliper Matching	7.07	7.04	0.031	0.252
		Kernel Matching	7.06	7.01	0.053	0.617
SH2 (Warm sub-humid lowlands)	LnProductivity	Nearest Neighbor Matching	6.93	6.90	0.028	0.339
		Stratification Matching			0.056	0.674
		Caliper Matching	7.13	6.91	0.217	.
		Kernel Matching	6.93	6.897	0.035	0.490
SM2 (Warm sub-moist lowlands)	LnProductivity	Nearest Neighbor Matching	7.34	7.17	0.168	1.075
		Stratification Matching			0.159	.
		Caliper Matching	7.26	7.196	0.068	0.176
		Kernel Matching	7.34	7.21	0.129	0.784
M2 (Warm moist lowlands)	LnProductivity	Nearest Neighbor Matching	7.35	7.24	0.110	0.447
		Stratification Matching			0.044	0.199
		Caliper Matching	7.69	7.53	0.161	0.560
		Kernel Matching	7.35	7.30	0.046	0.204
H4 (Cool humid mid highlands)	LnProductivity	Nearest Neighbor Matching	7.22	7.14	0.072	0.393
		Stratification Matching			0.022	0.157
		Caliper Matching	7.299	7.37	-0.075	-0.384
		Kernel Matching	7.22	7.18	0.039	0.252
SH3 (Tepid sub-humid mid highlands)	LnProductivity	Nearest Neighbor Matching	7.24	7.26	-0.014	-0.058
		Stratification Matching			0.136	0.975
		Caliper Matching	7.15	7.21	-0.067	-0.286
		Kernel Matching	7.24	7.19	0.054	0.348

***, **, * indicate significance at 1 percent, 5 percent and 10 percent level respectively.
Bootstrapped standard errors are based on 100 replications.
Source: Own computation, 2018

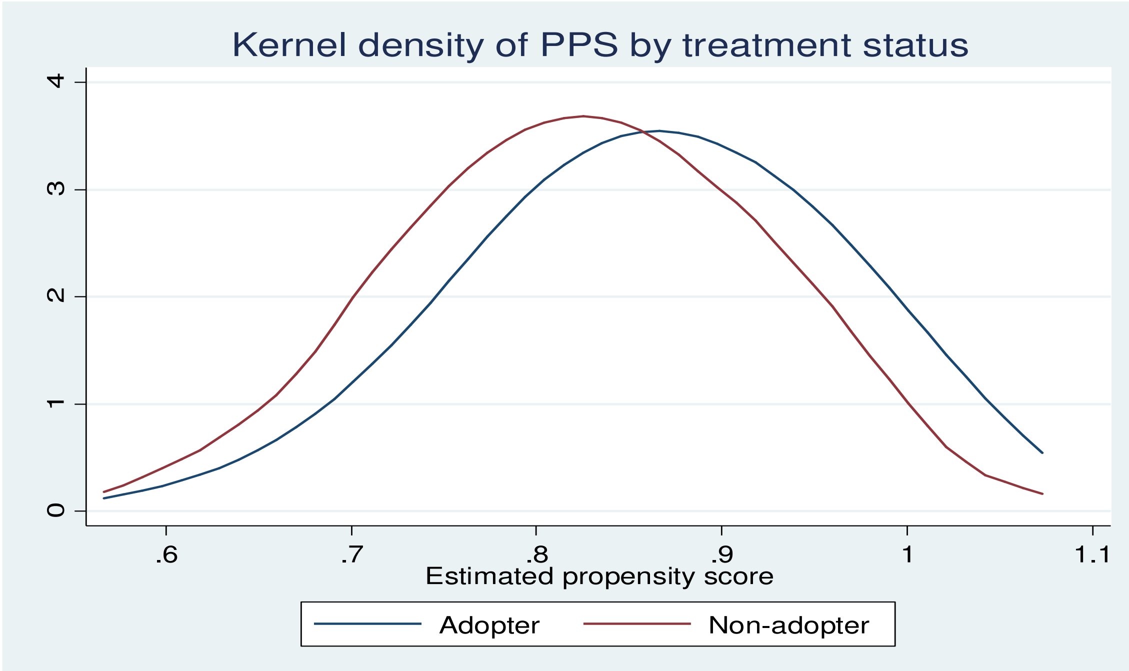

Figure 1(a): Distribution of propensity scores of adopters and non-adopters for SM3 (Tepid sub-moist mid highlands)

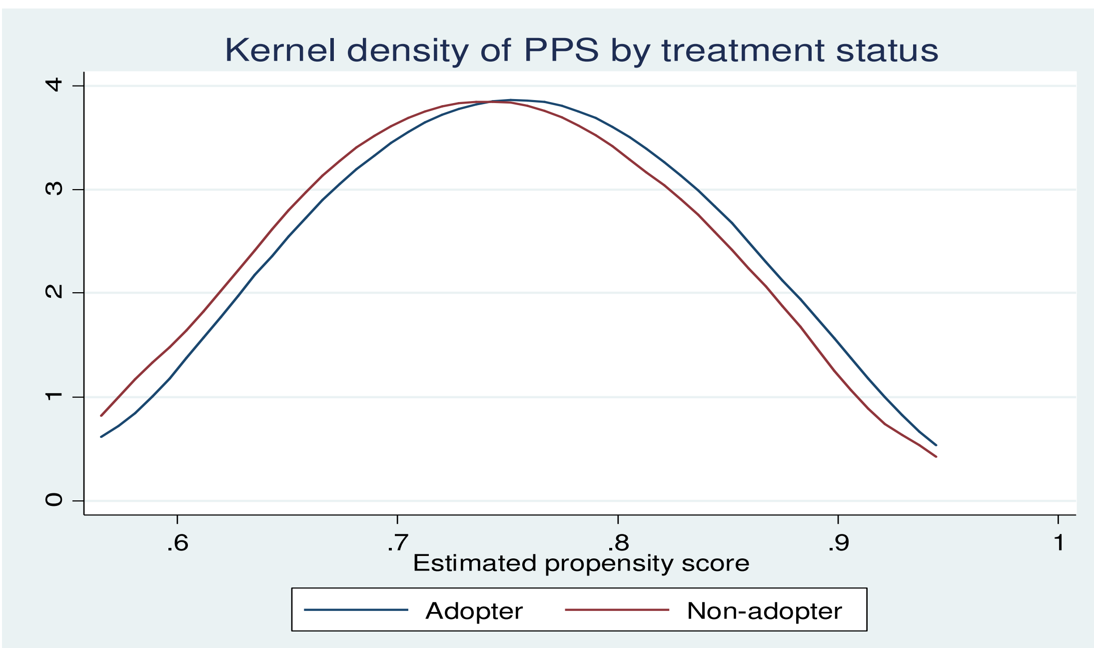

Figure 1(b): Distribution of propensity scores of adopters and non-adopters for H3 (Tepid humid mid highlands)

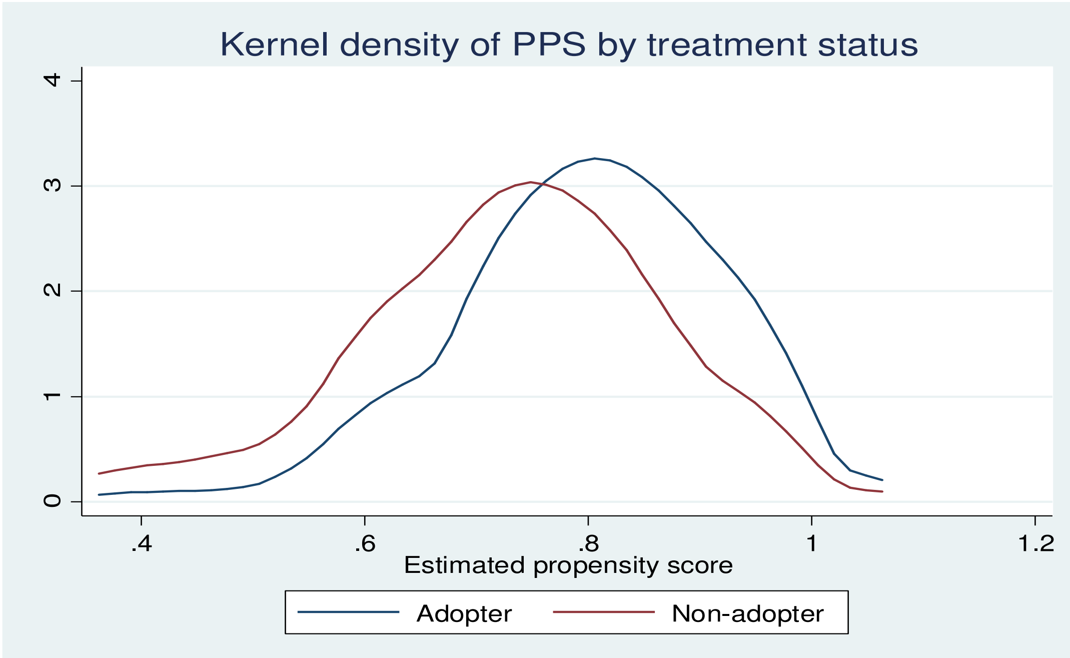

Figure 1(c): Distribution of propensity scores of adopters and non-adopters for M4 (Cool moist mid highlands)

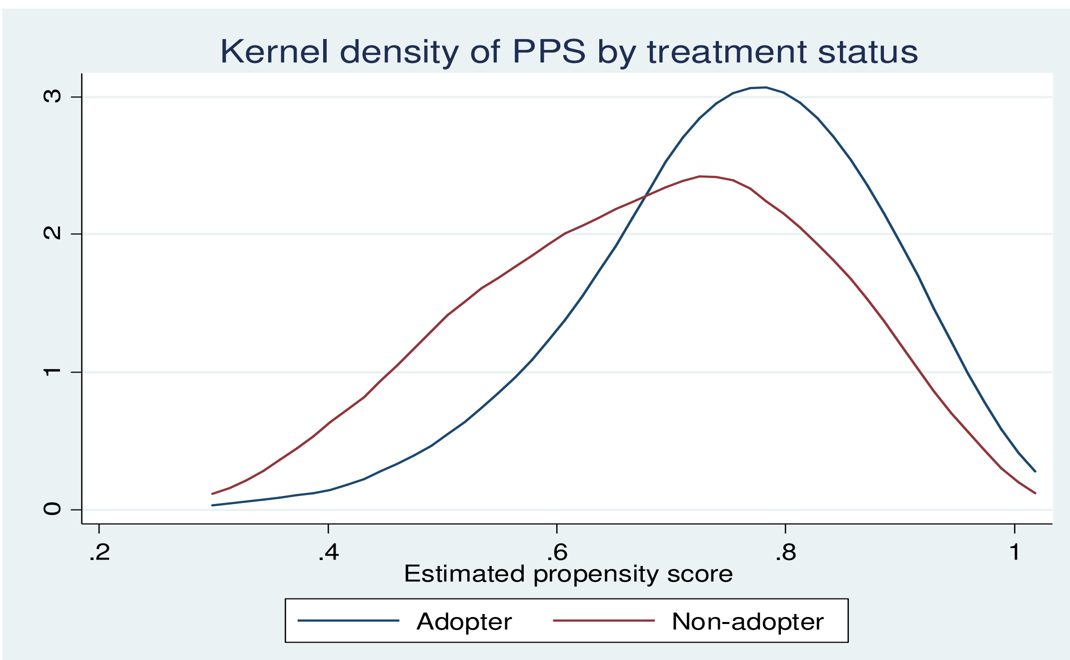

Figure 1(d): Distribution of propensity scores of adopters and non-adopters for M3 (Tepid moist mid highlands)

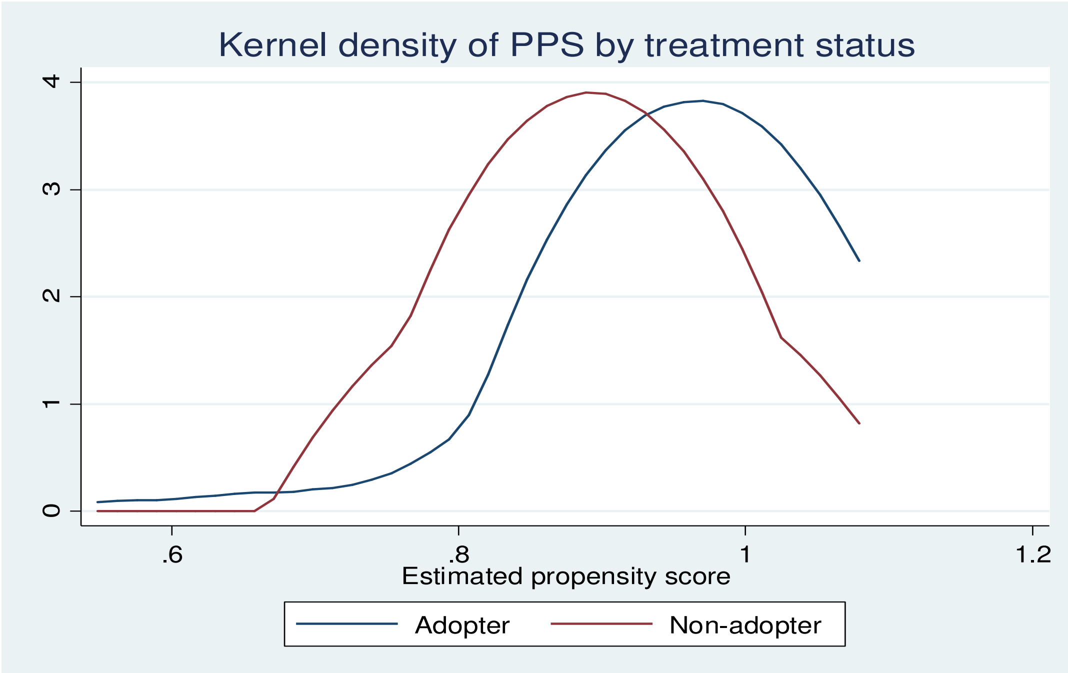

Figure 1(e): Distribution of propensity scores of adopters and non-adopters for SH2 (Warm sub-humid lowlands)

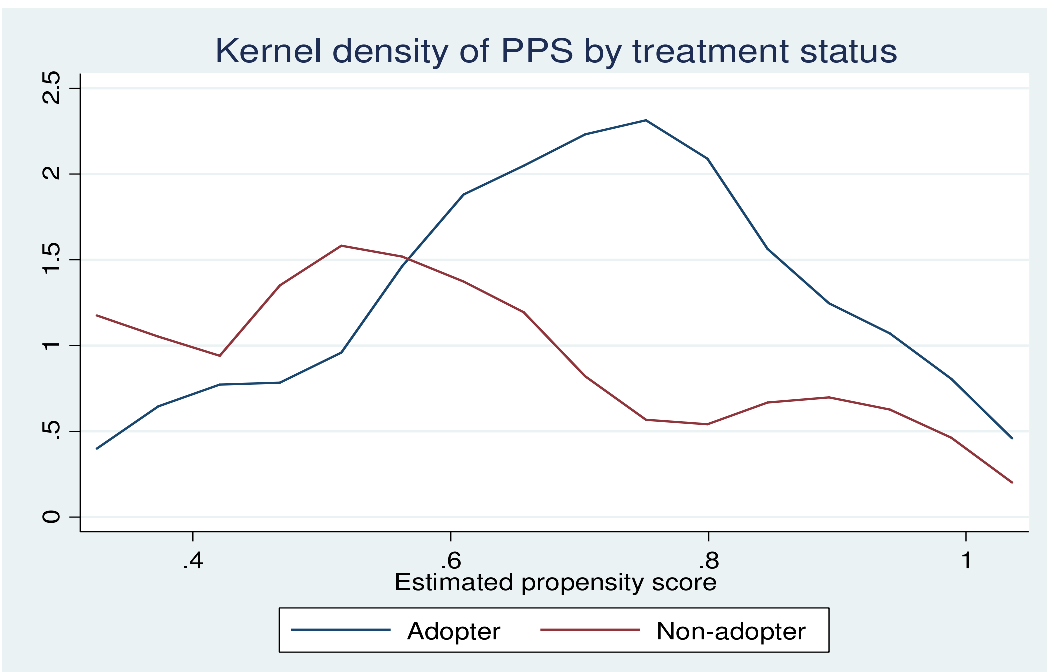

Figure 1(f): Distribution of propensity scores of adopters and non-adopters for SM2 (Warm sub-moist lowlands)

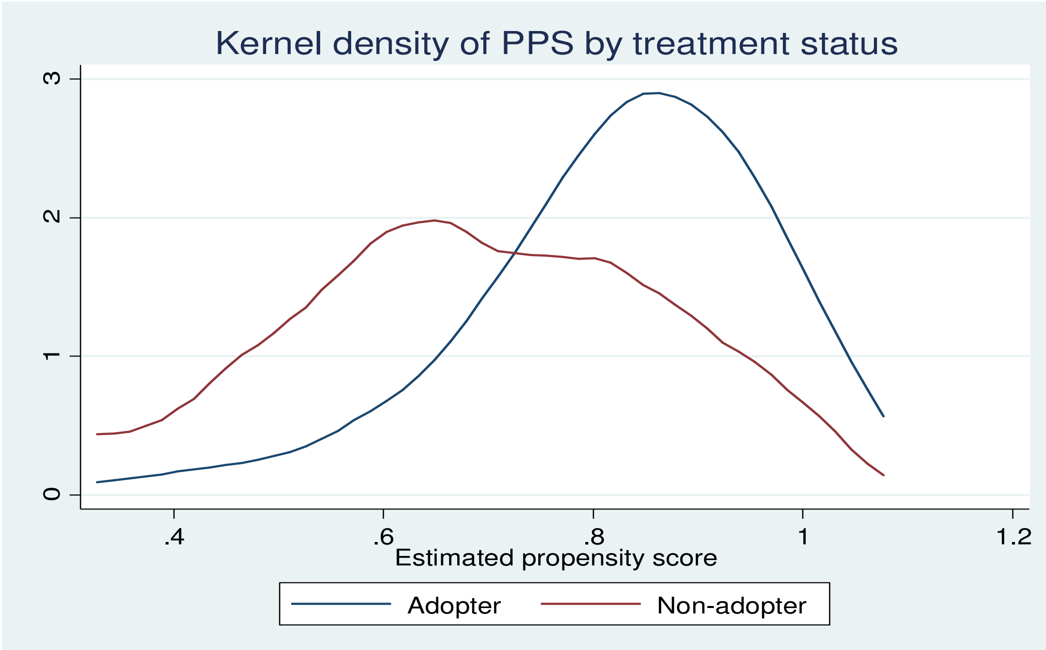

Figure 1(g): Distribution of propensity scores of adopters and non-adopters for M2 (Warm moist lowlands)

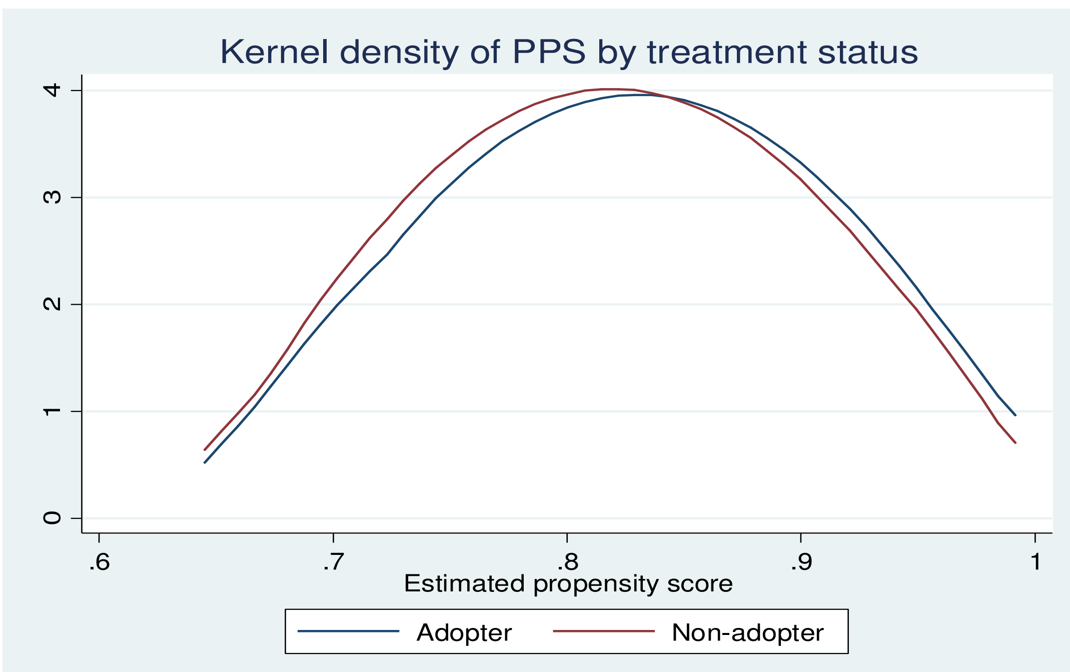

Figure 1(h): Distribution of propensity scores of adopters and non-adopters for H4 (Cool humid mid highlands)

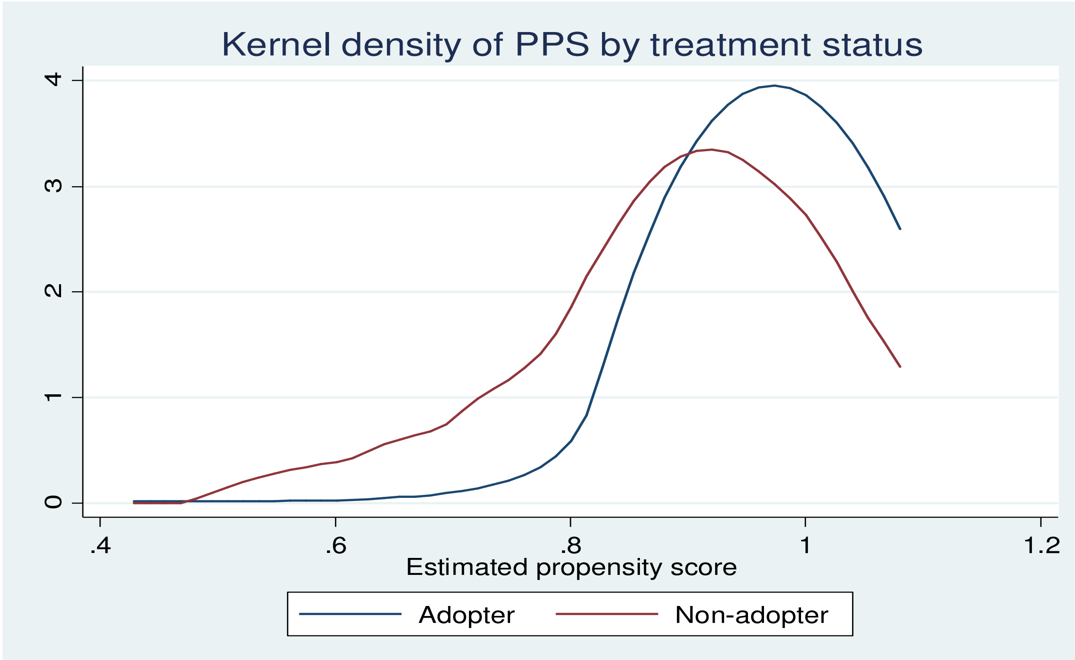

Figure 1(i): Distribution of propensity scores of adopters and non-adopters for SH3 (Tepid sub-humid mid highlands)

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