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Climate-Smart Agricultural Practices and Welfare of Rural Smallholders in Ethiopia

Does Planting Method Matter?

Amare Fentie and Abebe D. Beyene

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Abstract

The purpose of this study is to provide empirical evidence on the impact of a climate-smart agricultural practice (row planting) on the welfare of rural households. Data collected from 260 households in the North Wollo Zone of Ethiopia were analyzed using Propensity Score Matching (PSM) and a semi-parametric Local Instrumental Variable (LIV) version of the generalized Roy model. The results from the PSM revealed that adoption of row planting technology has a positive and significant impact on per capita consumption and on crop income per hectare. Covariates are well balanced and the effect of unobserved selection bias on the impact estimate is insignificant, indicating that the estimates are largely the effect of row planting. Similarly, the semi-parametric LIV model suggests that average treatment effect is positive and significant for crop income. Marginal benefit of row planting is increasing with higher propensity of the farmer to adopt this practice. Therefore, scaling up the technology will significantly contribute to farmers' resilience against the adverse effects of climate change through enhancing household's income and food security.

Key Words: row planting; Quncho Teff; Propensity Score Matching, semi-parametric LIV model.

JEL Codes: Q16, Q54, Q56

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Amare Fentie and Abebe D. Beyene*

1. Introduction

Adoption of climate-smart agricultural practices can sustainably increase agricultural productivity and incomes and, hence, build resilience against shocks, including adverse effects of climate change. Climate-smart agriculture has a huge potential in developing countries to reduce poverty and food insecurity through increasing agricultural production and incomes of rural households. In Sub-Saharan Africa, climate-smart agricultural practices are increasingly promoted to tackle the challenges of low agricultural productivity and the threats posed by greater weather variability and vulnerability to climate change (James et al., 2015). Climate-smart practices can range from farm level to international policy and financial mechanisms. However, at the farm level, wide-scale adoption remains a challenge, especially amongst smallholder farmers. We study the impact of a farm-level practice in rural Ethiopia – planting in rows instead of broadcast sowing – on per capita consumption and crop income per hectare. We thus contribute to a growing body of literature about the impact of such practices in the developing world. Rigorous study is needed of each potential climate-smart practice, and its application in a particular agro-ecological area, to inform policy makers about the magnitude of the impact and its potential to improve the welfare of rural farming communities.

More than 85% of Ethiopia's population depends on agriculture for their livelihood. The sector is characterized by low productivity and high dependence on weather. Currently, adoption of high-yield variety seeds and improved production technologies is on the top of the government's agenda for the successful achievement of its five-year Growth and Transformation Plan (GTP).

Despite the release of different improved varieties, farmers are still planting the improved varieties in a traditional way (broadcasting method). In recent years, the Government of Ethiopia, through the Agricultural Transformation Agency (ATA), rolled out a nationwide campaign to promote row planting for teff production, aiming to scale up

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adoption to about 2.5 million farmers. This method of planting is believed to be superior to the traditional way of planting seeds, but there is little empirical evidence on the extent to which it improves the welfare indicators of the rural farming communities. Therefore, the objective of this study is to estimate the welfare impact of row planting on rural smallholder farming communities in the Gubalafto *woreda* (district) of the Amhara region, using Propensity Score Matching and a semi-parametric Local Instrumental Variable (LIV) method. We measure the welfare impact in terms of consumption expenditure[1] and crop income of Quncho[2] teff per hectare.

The literature on the effects of climate-smart agricultural practices in developing countries like Ethiopia is scant. Most empirical studies in Ethiopia have focused on the impact of adoption of improved seeds, fertilizer, etc. on yield, income, poverty, and other welfare indicators of rural households (Kassie et al., 2010; Teklewold et al., 2013a; Teklewold et al., 2013b, Tekelewold et al., 2017; Beyene et al., 2017). To the best of our knowledge, there are few studies on ex-post impact assessment of adoption of row planting in Ethiopia. For example, a recent study by Minten et al. (2013) on the impact of row planting technology on farmers' teff yield, using an experimental technique, found that farmers who adopted row planting experienced increased yield. Our empirical work, however, uses observational data to see the effects of the row planting practice on two outcome indicators: crop income and consumption expenditure, by employing both Propensity Score Matching and semi-parametric local instrumental variable methods.

This study adds to the limited literature by analyzing the impact of row planting technology on two basic welfare indicators: crop income per hectare and consumption of farming households. Given that teff is one of the staple crops in the country in general and in the study area in particular, this empirical impact assessment study can inform policy makers and stakeholders about the effect of the practice on the welfare of rural farming communities.

[1] Here, the consumption expenditure refers to the total consumption expenditure per adult equivalent (i.e., the total household consumption expenditure is divided by the household size, in adult equivalent scales).

[2] Quncho Teff is an improved variety that is very common in the study area and the majority of the farming communities grow this variety. The lack of variation in varieties of Teff plays a role in estimating the true impact of the planting method.

2. Overview of Teff Production and Varieties in Ethiopia

Teff is the most significant food crop (in terms of both area and value) produced by Ethiopian farmers. It is estimated that teff accounts for 20% of all the cultivated land, covers over 2.7 million hectares, and is grown by 6.3 million farmers. Two out of three Ethiopians consume teff daily (Minten et al., 2013). It is a staple food for over 50 million people and occupies the largest place in the grain market (Tareke, 2009; Minten et al., 2013).

Teff is likely to remain a favorite crop of the Ethiopian population and the crop is also gaining popularity as a health food in the western world. Studies show that teff is a gluten-free crop, which makes it suitable for patients with celiac disease (Spaenij-Dekking and Koning, 2005). It is indigenous to the country and it is a fundamental part of the culture, tradition, and food security of its people. It is second only to maize in production and consumption. In Ethiopia, teff is mainly produced in Amhara and Oromia, with smaller quantities in Tigray and the Southern Nations, Nationalities, and Peoples (SNNP) region. There are 19 major teff-producing zones in the country. The central and south Tigray zones are the major teff-producing zones in Tigray.

Compared to other cereals, teff is a relatively low risk crop, as it can withstand adverse weather conditions under diverse agro-ecologies. In addition, the crop suffers from relatively few diseases and pest problems. Even though there are areas where the crop is grown during the short rainy season (*belg*), teff is mainly cultivated during the main rainy season (*meher*). It grows best between altitudes of 1,800 and 2,100 meters with an annual rainfall of 750-850 mm and a temperature range of 10-27 degrees centigrade, though it can also grow in much more varied areas, with rainfall up to 1,200 mm. The length of the growing period ranges from 60 to 180 days (depending on the variety and altitude) with an optimum of 90 to 130 days (Deckers et al., 2001). Agricultural research on improved teff varieties started in the mid-1950s, though investments have been limited and only a small number of improved varieties have been released, about 20 in total (Fufa et al., 2011). Improved varieties are increasingly popular in major teff growing areas of Ethiopia, though adoption is currently limited.

Despite the significance of the crop in terms of both production and consumption, yields are relatively low (around 1.2 t/ha), which is lower than the average yields of other cereal crops: maize (3.1 t/ha), rice (2.8 t/ha), and wheat (2.1 t/ha). In addition, high loss rates (25-30% both before and after harvest) reduce the quantity of grain available to consumers by up to 50% (Fufa et al., 2011). Given the scarcity of suitable arable land and the rapidly growing population, Ethiopia will need to scale up the adoption of yield-increasing technical innovations to ensure continued agricultural growth and to safeguard national food security (Minten et al., 2013).

The majority of planting in Ethiopia currently is done by hand-broadcasting, which not only uses significantly more seed than more modern methods, but also produces significantly lower yields. The use of mechanized planting technologies (such as row planters) not only reduces the time it takes to plant, but also increases yield by using the correct seed rates and evenly spacing seeds (ATA, 2013). However, the row planting method does not require farmers to use a sophisticated mechanical planter, rather simple homemade tools.

In 2011, the ATA's Teff Program started supporting on-farm productivity enhancement demonstrations, including new teff planting practices, such as row planting, reduced seed rates, and transplanting techniques. Beginning in four regions with 1,400 farmers at 90 Farmer Training Centers (FTCs), these demonstrations proved that yields can be increased up to 75%, on average, with some exceptional farmers producing up to 5.0 ton/ha. Row planting allows farmers to reduce the seed rate from 30 kg to 5 kg per hectare. Teff planted in rows do better due to reduced competition for water, sunlight, and soil nutrients. The spacing of rows also makes it easier to weed, harvest, and control pests and diseases. Each plant yields more stalks and more grains per stalk, which, when combined with the savings on inputs (seeds), leads to even higher potential net profits.

In sum, row planting is a climate-smart agricultural practice that can increase production significantly (Okiror, 2016). Doubling both the grain and the straw yield of teff would significantly contribute to Ethiopia's economy and food security.

3. Data and the Study Area

Gubalafto woreda has a population of 139,825, of which about 4% are urban inhabitants and about 96% are rural households whose livelihood depends on agriculture (CSA, 2007). Gubalafto has four agro-ecological zones: lowland (*kola*), mid-altitude (*woinadega*), highland (*dega*), and some areas above an altitude of 3,800 meters (*wurch*). The most commonly produced crops are annual crops such as teff, sorghum, maize, chick pea, haricot beans, and horse beans and cash crops such as onion and pepper. It is selected as a study site because teff is the dominant cereal crop and there are substantial numbers of users of improved teff seed variety with row planting. Recently, an intervention of the government to encourage row planting has aimed to double production in the woreda.

The main source of data for this study is information collected from sample farm households in Gubalafto woreda. Based on time, accessibility, financial constraints, and considering how well the sample size is representative, this study selected four Peasant Associations (PAs). To this end, a multistage sampling procedure was employed to select 260 Quncho Teff-producing households. To facilitate good matching, it is advisable to have a larger control group than treated individuals (adopters of the technology) among the samples selected for the survey. Hence, 104 adopters of the technology and 156 non-adopters (1.5 times higher than the number of the treated) were selected. In the first stage, Quncho Teff-producing farmers are purposively selected in the study area. The second stage involves the stratification of the farmers into two groups, consisting of adopters of row planting technology of Quncho Teff variety and non-adopters (Quncho Teff producers using the broadcasting planting method). The third stage is random selection of teff-producing farmers from each category of treatment status in each *kebele* (village) based on the proportion of farmers in each kebele. In the study woreda, there are five kebeles that are considered to be the best producers of teff: Woinye, Geshober, Lay Beles, Anova, and Gedo. Four of the five kebeles are considered for this study. The survey was conducted in September 2013. Data from sampled households was gathered through face-to-face interviews using a structured questionnaire.

4. Empirical Approaches

To facilitate the comparison of 'apples to apples', both Propensity Score Matching and a semi-parametric LIV model are employed. In addition, the semi-parametric LIV model is important in capturing heterogeneities and estimating the marginal treatment effect of row planting.

4.1. Propensity Score Matching

The greatest challenge in evaluating any intervention or program is obtaining a credible estimate of the counterfactual: what would have happened to participating units if they had not participated? Therefore, identification of the counterfactual is the pillar of a valid impact evaluation (Heinrich et al., 2010). If treatment is randomly assigned, the outcome of untreated individuals can be a good estimate of the counterfactual. However, if households that are treated have characteristics that differ from the ones that are not treated, comparison of the outcome between the two groups will yield biased estimates (Anderson et al., 2009). Without information on the counterfactual, the next best alternative is to compare outcomes of treated individuals or households with those of a comparison group that has not been treated. In doing so, one attempts to pick a comparison group that is very similar to the treated group, such that those who received treatment would have had outcomes similar to those in the comparison group, in the absence of treatment (Khandker et al., 2010).

4.2. Semi-Parametric Local Instrumental Variable (LIV) Model

Propensity Score Matching is not strong in capturing the effects of unobserved heterogeneity. To complement the findings of PSM, the semi-parametric LIV version of the generalized Roy model is used to estimate both the marginal treatment effect and average treatment effect given selection on unobservables and selection on returns[3]. We followed Brave and Wastrum (2014) for the semi-parametric LIV model. Unlike linear regression with endogenous treatment effects and maximum likelihood estimation of switching regression, the marginal treatment effects model produces both the marginal treatment effect and average treatment effect of the the adoption decision using both parametric and semi-parametric methods (Brave and Walstrum, 2014).

5. Results and Discussion

5.1. Descriptive Statistics

The summary of variables used in the empirical analysis is presented in Table 1 below. Of the total sample households, 40% of them planted and produced Quncho Teff using the row planting method in the 2012 cropping season. About 89% of sample households are male-headed and there is no significant difference in the mean of sex composition between adopters and non-adopters. As described in Table 1, some socioeconomic variables show significant mean variation between adopters and non-adopters of the new planting technology. Variables such as education, mobile phone ownership, livestock ownership, and income from the production of other crops are significantly different (at the 5% level) between adopters and non-adopters. Similarly, the mean values of the variables, household size, ownership of radio/television, number of oxen owned, contact with government extension agents, membership in farmers'

[3] The problem of selection on returns happens when the adoption decision of row planting and unobserved variables are essentially related (essential heterogeneity), which affects the return of the adoption (outcome variables), and it is this dependence that makes it relevant to examine the marginal effect of adoption of the climate-smart agricultural practice (row planting).

association, distance to the main road, and non-farm income are significantly different (at the 1% significance level) between adopters and non-adopters of row planting.

Table 1: Summary of Descriptive Statistics of Sample Households

Variable name	Non-adopters ($n = 156$) Mean (SE)	Adopters ($n = 104$) Mean(SE)	Diff (=mean of NA-Mean of Ad)
Age of household head	49.76(1.17)	47.8(1.07)	1.94
Gender of household head (1 if male, 0 if female)	0.87(0.027)	0.91(0.028)	-0.04
Education of household head (in years)	3.09(0.279)	4.05(0.33)	-0.958**
Household size (adult equivalent)	3.67(0.88)	4.32(0.129)	-0.66*
Ownership of radio/television	0.59(0.04)	0.76(0.042)	-0.17*
Mobile ownership (1 if the household has mobile phone, 0 otherwise)	0.69(0.037)	0.82(0.038)	-0.125**
Number of oxen owned	1.02(0.05)	1.28(0.06)	-0.26*
Other livestock ownership (in tropical livestock units/TLU)	0.58(0.048)	0.65(0.056)	-0.068
Application of pesticides (1 if yes, 0 otherwise)	0.48(0.04)	0.54(0.05)	-0.051
Contact with government extension (1 if there is contact, 0 otherwise)	0.78(0.033)	0.99(0.0096)	-0.21*
Income from other crops (in ETB)	5976.2(347.97)	7186(523.8)	-1210.1**
Access to credit (1 if yes, 0 otherwise)	.846(0.029)	0.9(0.029)	0.058
Membership in farmers' association (1 if member, 0 otherwise)	0.74(0.035)	0.9(0.029)	-0 .16*
Distance to the main market (in km)	53.95(2.83)	54.8(2.56)	-0.86
Distance to extension office (in km)	33.95(2.2)	32.58(1.88)	1.36
Distance to the main road (in km)	44.45(3.23)	29.94(2.71)	14.5*
Soil and water conservation (1 if yes, 0 otherwise)	0.91(0.023)	0.97(0.016)	-0.06***
Non-farm income (in ETB)	1599.62(335.2)	4050(702.2)	- 2450*
Farm size (in hectares)	0.453(0.016)	0.454(0.017)	-0.0012

* The numbers in parentheses are the standard errors.

Adopters of the row planting technology are more likely to be male-headed households, younger, more educated, and with larger household size, compared to non-adopters, though the mean difference in age and gender of household head is insignificant between the two categories of adopting status. The average educational level of the household head for adopters is about four years and it is about three years for non-adopters. In general, a higher educational level facilitates farming households' use of new agricultural technologies. In addition, about 76% of adopting households own a radio/television, compared to 59% of non-adopters.

Adopting farming households have higher mobile phone ownership, a higher average number of oxen, higher livestock ownership, and greater access to credit (though the difference is insignificant) compared to non-adopters. It is believed that better endowment of information sources, higher income, and better access to credit institutions helps farmers adopt new farming technologies.

The average household size for the sample households is about 4 people, which is lower than the national average of 4.8 (MOH, 2011). The average farm size of households is 0.45 ha and there is an insignificant difference in land holdings between adopters of row planting (0.454 ha) and non-adopters (0.453 ha). The mean non-farm income of row planting households and broadcasters is 4050 and 1599 Birr, respectively, which is statistically significant. The average income obtained from the production of other crops is about 5776 and 7186 Birr for broadcasting households and row planters, respectively.

The other important variable is the outcome variable of interest, which is per capita consumption.[4] There is a significant difference in per capita consumption expenditure between the two groups of households (i.e., adopters and non-adopters). The average per capita consumption of row planters and broadcasters equals 7765.36 and 6077.66 Birr, respectively. Crop income per hectare[5] is the other welfare indicator used in this study. The mean crop income per hectare of row planting households equals 8970.769 Birr and for broadcasting households, it is 7678.369 Birr, with a significant difference (at the 10% level).

In addition, sample farming households were asked about their perception of row planting practice. Adopting households were asked why they use row planting production technology. Accordingly, 96% of adopting households responded that better productivity of the technology is the main reason for their adoption. The second most important reason

[4]To get the monetary value of per capita consumption, we use the local market price for each food item at the time of the survey.

[5]In the calculation of crop income per hectare, the yield of Teff is reported in terms of kilograms. Here, the per-kilo value of Teff is calculated and multiplied by the total amount of yield in terms of kilograms produced. 16 birr/kg is the current market price at the time of the data collection.

for using row planting technology is no lodging (81%). Lodging is the permanent fall of the crop during its time of maturity which negatively affects the crop yield. Since teff has tall, tender stems that can easily fall over, it is the most common problem for farmers, especially those who produce teff using the traditional planting method (broadcasting). Row planting, therefore, reduces lodging and enhances productivity. The other reasons for adoption are lower seed rate (74%), lower fertilizer requirements (59%), less erosion (39%), and lower weeding cost (13.4%).

The non-adopting households were asked why they use the traditional broadcasting method rather than row planting. The majority of non-adopters (92%) responded that they did not use row planting because it is labor demanding. This shows that there is a need to think about less labor-intensive technology in order to address the labor shortage problem of some households and enhance the take up rate of the technology. In addition, about 18% of non-adopters did not believe that row planting would give better yield than the traditional broadcasting method. The other reasons for not using the row planting technique were the time consuming nature of it (46.7% of non-adopters) and lack of awareness about the technology (23.7%). This may suggest that better information about the technology could influence non-adopters to adopt the technology.

In the following sections, results from both the PSM and semi-parametric LIV method are discussed.

5.2. Estimation of the Treatment Effects and Sensitivity Analysis

Estimating the propensity score is important for two reasons. The first one is to estimate the average treatment effect on the treated (ATT). The second is to obtain matched treated and non-treated farming households. Logistic regression is used to estimate the propensity scores.

5.2.1. Estimation Results of the Determinants of Adoption

The results of the logit estimates of row planting technology of Quncho Teff and the covariates that are used in the matching process are reported in Table 2. The overlap condition was also imposed and the balancing property was set and satisfied. Among row planters, the predicted propensity score ranges from 0.0767 to 0.979 with a mean of 0.54, while among broadcasters, it ranges from 0.0023 to 0.912 with a mean of 0.31. Thus, the common support condition is satisfied in the region of [0.0767, 0.979] with a loss of 34 observations (about 13% of the total sample) from non-adopters of row planting technology. The model has a pseudo R^2 value of 0.194 and log likelihood value of -141.

The coefficients of most of the variables have the expected signs and they include covariates such as household size, ownership of radio, contact with government extension agents, and distance to the main road, among others.

The coefficient for family size, which is used as a proxy for labor availability in the household, is positive and significant at the 1% level. Larger household size implies higher availability of labor, which can facilitate the adoption of agricultural technology. Ownership of a radio has a positive and significant impact, suggesting that farm households that own a radio have a higher probability of adopting row planting than those that do not. Ownership of a radio can help the farmer access information about the row planting technology and, hence, it can enhance technology adoption.

The other important factor influencing row planting technology adoption is farm households' contact with government extension agents. As expected, the more contact a household has with government extension agents, the more easily it can access information about technology; hence, it is positively and significantly correlated with adoption of row planting. Contact with government extension agents exposes farmers to information, which can facilitate the adoption of agricultural technology (Cole and Fernando, 2016; Kinuthia and Mabaya, 2017). Non-farm income is another important variable affecting adoption positively and significantly. With higher non-farm income, farmers become more likely to undertake the risk of adopting a new technology (Ayinde, 2008). Hence, non-farm income can augment household income and can influence households' adoption decision and consumption expenditure.

Table 2: Estimation of the Logit Model

Variables	Estimates
Age of household head	-0.0078(0.0144)
Sex of household head	-0.1020(0.5031)
Education of household head	0.0344(0.5326)
Household size (PE)	0.44***(.1360)
Ownership of radio/television	0.5418(0.3259)
Mobile ownership	-0.0286(0.3743)
Number of oxen owned	0.2965(0.2818)
Livestock ownership (TLU)	-0.2834(0.2859)
Contact with government extension	3.17***(1.0524)
Income from other crops	0.00002(0.0003)
Access to credit	0.6741(0.4574)
Membership in farmers' association	0.0657(0.4705)
Distance to extension office	0.00089(0.0070)
Soil and water conservation	0.96(0.7543)
Non-farm income	0.00007**(0.00003)

Note*:* The common support option has been selected. The region of common support is [.07670635, .97903421]

5.2.2. Covariate Balancing Tests

A covariate balancing test is required after matching to make sure that the differences in the covariates in the two groups of matched samples are eliminated, for the matched group to be plausibly counterfactual (Ali and Abdulai, 2010). Among different versions of balancing tests, the most widely used balancing test is the mean absolute standardized bias between adopters and non-adopters suggested by Rosenbaum and Rubin (1985). They recommended that a standardized bias difference of greater than 20% should be considered too large and an indicator of failure in matching.

The sample differences in the raw data (unmatched) significantly exceed those in the samples of matched cases. Hence, the process of matching creates a higher degree of covariate balance between row planters and broadcasters. In addition to the standardized bias measure, we used other balancing indicators, such as the likelihood ratio test of the joint significance of all covariates and the pseudo R^2 from the logit of treatment status on covariates before matching and after matching on matched samples (Caliendo and Kopeinig, 2008). After matching, there should be no systematic differences in the distribution of covariates between the two groups; hence, the pseudo R^2 should be fairly low and the joint significance of all variables should be rejected. Therefore, the distribution of covariates after matching, the low pseudo R^2 (0.014), and the insignificant p-value (0.995) of the likelihood ratio show that covariates are balanced across the two groups of farming households. The common support graphing also shows that there is substantial overlap between adopters and non-adopters of row planting technology.

The imbalance between row planters and broadcasters in terms of the propensity score amounts to more than 65% before matching. However, the bias was significantly reduced to below 4% after matching. As portrayed in the balancing test, before matching, several variables show significant differences, while after matching, they are balanced. The covariate balancing indicators such a low pseudo R^2, insignificant p-value of the likelihood ratio test, and the mean standardized bias, which is well below 20%, supports the hypothesis that row planter and broadcaster farming households have the same distribution in covariates after matching.

5.2.3. Estimation of Treatment Effects

The effect of row planting technology for Quncho Teff-producing farming households on per capita consumption expenditure and crop income per hectare is estimated using three alternative matching algorithms and ATT is compared among these algorithms. The matching techniques are nearest neighbor matching (with replacement), kernel matching, and radius matching. Bootstrap standard errors based on 100 replications are used.

All the three matching algorithms showed that adoption of row planting technology had a positive and significant effect on per capita consumption and crop income. Table 3 shows the estimation of average treatment effects on the treated (ATT) from the three matching algorithms. The outcome variable is log of per capita consumption[6]. The increase in per capita consumption ranges from 12.3% to 18.4% higher for row planting households compared with broadcasters. This is the average difference in per capita consumption of similar farming households that belong to different treatment statuses (users of row planting and broadcasters).

Although the three matching algorithms based on the logit model produced somewhat different quantitative results, the qualitative findings are similar. The results in

[6]The log of per capita consumption per adult equivalent is used for the normalization of the outcome variable.

Table 3 indicate that the adoption of row planting of Quncho Teff varieties have a positive and significant impact on the per capita consumption expenditure. The increasing impact of the row planting technology thus helps the users of the technology to reduce their consumption poverty. Similarly, Table 4 shows that the row planting technology has a positive and significant effect on crop income per hectare. The treatment effect ranges from ETB1323.1 (72.3 USD)[7] to ETB2116.5 (115.65 USD) higher crop income for the adopters compared to the non-adopters of the row planting technology. This particular finding on crop income is consistent with a recent finding by Minten et al. (2013). Their finding indicated a positive impact of row planting on yield of the crop.

Table 3: Estimation of ATT: Effect of Row Planting of Quncho Teff Variety on per Capita Consumption

	Nearest neighbor	Radius (0.1)	Kernel
ATT	18.4	12.3	13.4
SE	0.07	0.053	0.057
T value	2.63	2.34	2.34
Treated	104	104	104
Control	54	122	122

Table 4: Estimation of ATT: Effect of Row Planting Technology of Quncho Teff Variety on Crop Income per Hectare

	Nearest neighbor	Radius (0.1)	Kernel
ATT	2116.5	1323.1	1540
SE	916.75	760.5	673.19
T value	2.3	1.74	2.29
Treated	104	104	104
Control	54	122	122

7 1 USD = 18.3 Ethiopian Birr in 2012.

5.2.4. Sensitivity Analysis

Matching estimators are not robust against hidden bias. Since estimating the magnitude of selection bias with non-experimental data is not possible, we address this problem through a method proposed by Rosenbaum (2002). Rosenbaum (2002) proposed the Rosenbaum bounding approach in order to check the sensitivity of the estimated ATT with respect to deviations from the CIA.

Table 5: Result of Sensitivity Analysis using Rosenbaum Bounds for Log of per Capita Consumption

Rosenbaum bounds for log of consumption expenditure (N = 260 matched pairs)						
gamma	Sig+	Sig-	t-hat+	t-hat-	CI+	CI-
1	0	0	8.69926	8.89926	8.66299	8.73492
1.25	0	0	8.67008	8.72693	8.63272	8.76477
1.5	0	0	8.64678	8.75147	8.60915	8.78976
1.75	0	0	8.62671	8.77075	8.58825	8.80999
2	0	0	8.6101	8.7886	8.57063	8.82861

*gamma - log odds of differential assignment due to observed factors

Sig+ - upper bound significance level

Sig- - lower bound significance level

t-hat+ - upper bound Hodges-Lehman point estimate

t-hat- - lower bound Hodges-Lehman point estimate

CI+ - upper bound confidence interval (a = .95)

CI- - lower bound confidence interval (a = .95)

Table 6: Result of Sensitivity Analysis using Rosenbaum Bounds for Crop Income per Hectare

Rosenbaum bounds for log of crop income (N = 260 matched pairs)						
gamma	Sig+	Sig-	t-hat+	t-hat-	CI+	CI-
1	0	0	7466.67	7466.67	6933.33	8000
1.25	0	0	7120	8000	6400	8400
1.5	0	0	6666.67	8000	6400	8800
1.75	0	0	6400	8533.33	6133.33	9333.33
2	0	0	6400	8800	5866.67	9600

*gamma - log odds of differential assignment due to observed factors

Sig+ - upper bound significance level

Sig- - lower bound significance level

t-hat+ - upper bound Hodges-Lehman point estimate

t-hat- - lower bound Hodges-Lehman point estimate

CI+ - upper bound confidence interval (a = .95)

CI- - lower bound confidence interval (a = .95)

The results of the Rosenbaum bounds sensitivity analysis are reported in Tables 5 and 6. Given that the estimated adoption effect of row planting technology is positive, the lower bounds under the assumption that the true treatment effect has been underestimated were less interesting (Becker and Caliendo, 2007).

The results from the semi-parametric LIV are reported in the Appendix. The findings are similar to the Propensity Score Matching with positive average treatment effects. In addition, the marginal treatment effect is increasing with higher propensity of households to join the treatment status (i.e., row planting).

6. Conclusion and Policy Implications

The relationship between climate-smart agricultural practices and the welfare of rural farming households is complicated and there is scant empirical evidence. Though the positive effect of agricultural technology on welfare is widely accepted, assessing the impact of agricultural technology adoption at the micro level is challenging due to the difficulties in finding appropriate methods to quantify the impact of agricultural technologies. This study tried to assess the contribution of row planting technology to per capita consumption expenditure and crop income per hectare using both Propensity Score Matching and semi-parametric LIV methods. We used survey data collected from 260 rural farming communities in the Gubalafto woreda of the Amhara region of Ethiopia.

Our results show that row planting technology has a positive and significant impact on per capita consumption and crop income per hectare of farming households. The estimation of the causal impact using Propensity Score Matching suggests that row planter households have higher per capita consumption and crop income than broadcasting households. The sensitivity analysis shows that the sensitivity of the estimated treatment effect to unobserved heterogeneity is insignificant and that the observed effect is largely from row planting. The findings from the semi-parametric LIV model also show that the marginal treatment effect on crop income is increasing with higher propensity to adopt the row planting method.

In addition, the majority of the sampled farming households use row planting, primarily due to its role in enhancing productivity, absence of lodging, and lower seed rate. The labor-intensive nature of the technology and lack of awareness about the method are the main constraints for the adoption of row planting.

The results of the study generally confirm the potential role of this climate-smart agricultural practice for the welfare improvement and resilience building of farming communities. Future studies, going beyond cross-sectional data, may assess the dynamics of the effect of the row planting practices.

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