

INNOVATIONS

Content available on Google Scholar

Home Page: www.journal-innovations.com

Impact of Row-Seeding Technology Adoption on Teff Productivity, Household Welfare and asset holding: Evidence from South West Shoa Zone, Oromia Regional State, Using Propensity Score Matching Technique

Tesfaye Gedefaw Wolde

School of Business & Economics, Department of Economics
Ambo University, Ambo, Ethiopia

Corresponding Email: tesfayewgw@gmail.com

Abstract

Due to the imbalance between increasing population increase (drivers of demand for crop products) and availability of agricultural crop products, food insecurity has been one of Ethiopia's long-standing societal concerns. Demand for agricultural crop goods such as maize, wheat, and teff is increasing. Teff is currently one of the most popular foods, with demand increasing on a regular basis not just in the United States, but also internationally. As a result, there is a discrepancy between Teff output and demand in Ethiopia. To correct this imbalance, development agencies such as agricultural development centers use various yield-increasing technologies such as compost, fertilizer, and pesticides over a long period of time, phase by phase. A new common technology known as row seeding technology was recently established by agricultural research agencies. Because it reduces seed rate, creates more space between seedlings, allows for weeding, reduces competition between Teff seedlings, and allows for greater branching out of Teff plants, row planting technology can boost Teff yields. At the pilot stage at several agricultural research centers and farmer training centers, the productivity of row-planting technology was assured. The success of this technique at the home level, however, is determined by factors such as technological acceptance perfection, manpower availability, soil quality and type, and institutional considerations. As a result, the success of row-seeding technologies should be assessed at the household level utilizing impact evaluation methodologies such as Propensity score matching (PSM). The goal of this study is to evaluate how row-seeding technology affects Teff productivity, household wellbeing, and

asset holding. The study relies on cross-sectional data acquired at the household level via structured interviews. Data was obtained from 100 adopters and 100 non-adopters and analyzed using both descriptive and analytical methods (PSM). Row seeding technology can produce a considerable difference in Teff output, asset holding, and welfare indicators between adopter and non-adopters, according to both descriptive and analytical approaches. As a result, development agents should make greater efforts to expand the reach of row-planting technology to all households in order to achieve food security and improve rural households' living conditions.

Key words: 1. Impact, Row-planting technology 2. Household's welfare 3. Productivity 4. Rural households

Introduction

A key issue of economic development theory is a historical study of how individuals are able to break out of the poverty cycle. Around 75% of the world's poor people (those who survive on less than a dollar per day) live and work in rural areas, and their livelihood is largely dependent on agricultural production (Mendola, 2007). Similarly, in Ethiopia, over 83 percent of the population lives in rural areas, and agriculture is the primary source of income, with agriculture accounting for the largest proportion of employment opportunities, a substantial share of GDP, and a source of foreign earnings (NBE, 2013; CSA, 2013). Ethiopia is a developing country in Sub-Saharan Africa with a high population growth rate and a long history of food insecurity. According to population projections, the number of people living per square kilometer will increase from 35 in 1950 to 270 in 2050, resulting in a higher incidence of land fragmentation and, as a result, a reduction in agricultural production (Menberu, 2014). Chronic food insecurity has resulted in Ethiopia due to a series of production failures and an imbalance between agricultural productivity and population increase (Kaluski et al., 2001). As a result, because agriculture is so important to the livelihoods of more than half of the world's people, agricultural growth is considered as the best option for achieving food security. By increasing the amount of food available for consumption, agricultural production growth can help to alleviate food insecurity. Extensification (i.e., expanding acreage) and intensification (i.e., increasing crop yields) are two methods for increasing agricultural output (i.e. by using more inputs and technologies per unit of land). However, in most food-insecure nations, where severe population pressure is a significant bottleneck, extensification is not a realistic method for increasing agricultural production. Because land is scarce, intensification, which entails investments in modern inputs and technologies, is a better option for increasing agricultural production and reducing food insecurity. Several Asian countries successfully implemented this option in the 1970s, and it was dubbed the "green revolution" (Mulugeta et al, 2012).

Considering the shortage of farmland, the Ethiopian government's 1991 economic growth strategy places a strong focus on boosting agricultural expansion in order to achieve food

security and poverty alleviation. This method focused on technology packages that integrated credit, fertilizers (compost and chemical fertilizer), improved seeds, and better management procedures to increase cereal yields (Endale 2010). Ethiopia has lately had one of the most significant agricultural development spurts in SSA; nevertheless, continuing this high rate of growth will necessitate the successful implementation of new yield-increasing technologies (Dadi et al. 2004; Dorosh and Rashid 2012).

In developing countries, new agricultural technologies and improved practices are critical for increasing agricultural production (and hence improving national food security). Adoption of enhanced agricultural technologies, if effective, might boost total economic growth by creating inter-sectoral links while conserving natural resources (Abdulai and Tietje 2006, Sanchez, et al 2009). Traditional sowing technology, particularly Teff, has recently been claimed to be a fundamental impediment to enhanced cereal yield (Fufa et al. 2011). Teff is usually planted by broadcasting or dispersing Teff seed at a high seed rate by hand. Alternative planting methods, such as row planting seeds or transplanting seedlings, are considered as superior to standard broadcasting because the seed rate is reduced and greater space between plants is provided (Fufa et al. 2011).

Experiments in controlled settings have revealed that these alternate planting strategies have a considerable and favourable impact on Teff yields (Fufa et al. 2011). As a result, in 2013, the Ethiopian government launched a statewide effort to encourage the use of improved Teff production technology, such as row planting, with the goal of reaching over 2.5 million Teff farmers. Row-seeding technique increases productivity since distributing seeds by hand at a high seed rate impedes Teff yields by making weeding difficult and increasing competition with weeds and other Teff plants, which can reduce nutrient intake by Teff plants.

Different agricultural experts agreed that row-seeding technology increased productivity at the pilot level under fully controlled experiment circumstances. Productivity, on the other hand, is influenced by a variety of factors, including environmental elements such as soil type, agroecological parameters, and land gradient; institutional factors such as labor availability, proper technological imitation, farmer experience, and other considerations. Farmers may not receive enough and sufficient development assistance, as well as ongoing follow-up from development agents. As a result, once the technology is released to the farmer, researchers must undertake farm-level study to determine its usefulness in terms of productivity and household welfare. Now we need to perform farm-level research to see either row-seeding boosts output per hectare and household wellbeing or not at the grass-roots level. The farm level impact study will provide useful information for determining whether or not the technology can be utilized effectively by the farmers. So far, no research has been done in the study area, specifically on the influence of row seeding technology adoption on productivity and household welfare. As a result, the purpose of this research is to assess the impact of row-planting technology adoption on productivity, household welfare, and other factors that influence adoption decisions.

Research methods and Materials

Study area and data sources

The study conducted in South West Shoa Zone which is one of the eighteenth zones in the Oromia Regional State. South west shoa zone consists of eleven districts (woreda administration). According to the SWSARDO 2013/14 report, row-seeding technique in Teff cereal was used on 26 069 hectares of land, with the technology being widely applied in three districts: Qersa, Woliso, and Wanchi, as compared to the other woredas in the zone. Primary data on household demographic composition, output per hectare, consumption expenditure (food and non-food expenditure), off-farm income, physical capital variables of the household including livestock holding, human capital variables, soil type, quality of the land, steepness of the parcel, amount of fertilizer, seed, chemicals, manpower, and oxen d were collected from rural households in Qersa, Wanchi, and Woliso districts.

Sampling method

Purposive and random sample approaches were used in the study. To begin, choose three districts based on the extent to which row planting technology has been widely adopted. Second, choose one Kebele from each district and identify the households that used row planting technology in the primary production season of 2015 (especially on Teff cereal), as well as those that did not. The sample size for this study was 200 households, based on the number of explanatory factors included in the econometric analysis (which is 100 adopters and 100 non-adopters). Finally, a random sample of households was chosen using a systematic random selection method.

Method of analysis

For data analysis, the study used both descriptive and analytical methods. In terms of productivity, consumption expenditure, land size, demographic composition, and other indicators, a descriptive method is used to compare adopter and non-adopter groups. Propensity score matching is an econometric method that is chosen because it is more appropriate than other effect evaluation strategies.

Propensity Score Matching (PSM) Method

Estimating the impact of technology adoption on non-experimental observation is more difficult than estimating the impact of experimental treatments, because the former requires the counterfactual outcome, which refers to what would have happened if the participant had not participated or if non-participants had participated. The impact of row-seeding technology adoption on outcomes such as productivity and household welfare is simply assessed using a dummy variable that refers to households that have accepted new technology on the productivity and welfare equation in the naive estimation. This approach, however, produces biased estimations if potential endogeneity issues are not addressed. Row planting technology may not be distributed randomly, thus households may choose to adopt or not adopt based on their perspective or information about what they will have. Farmers' decisions to adopt or not adopt are based on individual self-selection, and adopters and non-adopters may exhibit fundamentally distinct features.

Adopters may choose to employ row-seeding technology based on the benefits they expect in the future and the information they will have.

Mathematically the two-outcome equation will be specified as follows:

$$Y_i = \alpha + \beta X_i + \delta D_i + \epsilon_i \quad \text{Productivity equation (output per hectare)}$$

$$C_i = \beta_0 + \beta_1 X_i + \gamma D_i + \epsilon_i \quad \text{Welfare equation (consumption expenditure as a proxy)}$$

Since there will be some other factors that are connected with technology adoption and some omitted variable that impacts the welfare of the household and productivity (recorded in the error term, ϵ), employing a simple ordinary least square estimator on the above two equations generates biased estimates. To determine the true impact of technology adoption, we opted to employ propensity score matching approaches. When comparing participant outcomes with and without treatment in a program assessment setting, propensity score matching is frequently employed. The strategy was originally offered as a way to eliminate bias in treatment effect estimation. A propensity score was defined as a conditional chance of obtaining a therapy based on pre-treatment variables. The objective is to first construct an index that combines observable household factors into a propensity score index based on the likelihood of adopting technology. As a result, the households are divided into two groups: those who accept the new technology (treatment group) and those who do not (control group), and their propensity scores are used to rank them. Finally, households in the treatment group are matched with households in the control group in such a way that households who embrace new technology are compared to households with similar propensity scores that do not. According to (Gilligan et al., 2008), the untreated group has the same average outcome as the treated group would have had they not received the program after controlling for all pre-intervention observable household and community characteristics that are correlated with both program participation and the outcome variable.

Assuming that we have some individuals participating in the program and some others who are not, and denoting the outcome variable of the treated individual by Y_{1i} and that of the non-treated by Y_{0i} , we can put the effect of treatment as $(Y_{1i} - Y_{0i})$. For a group of individuals, we need to use averages of outcomes across all the treated and non-treated, which will then give us the expected value or average effect of treatment. This is known as Average Treatment Effect (ATE) in the evaluation literature (Wooldridge, 2002; Cameron and Trivedi, 2005).

Thus, for a population we have the following with E standing for expected value or mean:

$$T_{ATE} = E(Y_{1i} \text{ or } C_{1i} | X, d_i = 1) - E(Y_{0i} \text{ or } C_{0i} | X, d_i = 0)$$

where T_{ATE} represents the average difference in outcomes between households with adopting technology and households without the new technology.

The sample equivalent of the above equation is given as follows:

$$T_{ATE} = \frac{1}{n} \sum_{i=1}^n (Y_{1i} \text{ or } C_{1i} | X, d = 1) - E(Y_{0i} \text{ or } C_{0i} | X, d = 0)$$

Because it examines the expected effect of treatment on a random sample of the population, including people who may not be eligible for treatment, the ATE has limited policy implications (Wooldridge, 2002).

As a result, the interest measurement is usually the one that determines the average gain in program participation (treatment) on the treated as a result of the treatment. Impact is measured in this case by the difference in the outcome of interest between what is happening with participation and what would have happened if the program had not been implemented. Denoting program participation or treatment by D_i (where $D_i = 1$) indicates treatment and $D_i = 0$, non-treatment), and program outcome by Y , the effect of treatment on the treated for an individual is obtained by $(Y_{1i} - Y_{0i} | D_i = 1)$. This equation expresses program impact as a difference between the outcome for an individual with the program (Y_{1i}) and without the program (Y_{0i}) given that the individual under study is participating in the program (i.e., where $D_i = 1$). Averaging across the population, we obtain the average effect of treatment on the treated (ATT), which is given by:

$$ATT = E(Y_{1i} \text{ or } C_{1i} | d_i = 1) - E(Y_{0i} \text{ or } C_{0i} | d_i = 1)$$

The sample equivalent is:

$$ATT = \frac{1}{n} \sum_{i=1}^n (Y_{1i} \text{ or } C_{1i} | X, d = 1) - E(Y_{0i} \text{ or } C_{0i} | X, d = 1)$$

While the outcome of what has happened to the individual participating in the program (i.e., $Y_{1i} | D_i = 1$) is indeed observable, the outcome of what would have happened to the same individual without the program (i.e., $Y_{0i} | D_i = 1$) is not observable. We never observe an individual in two different conditions at the same time (Ravallion, 2001; Heckman et al., 1998; Hahn, 1998; Wooldridge, 2002; Cobb- Clark and Crossley, 2003; Cameron and Trivedi, 2005). Thus, for a program participant we can only observe the outcome variable with the program, and for a non-participant, we can only observe outcome without the program. There exist an apparent difference between what we want to measure, and what we directly observe from our sample. Speaking in terms of means, while, as indicated above, what we want to measure is given by $ATT = E(Y_{1i} | D_i = 1) - E(Y_{0i} | D_i = 1)$, what we can directly observe from a sample for the treated and non-treated is $E(Y_{1i} | D = 1)$ and $E(Y_{0i} | D = 0)$. The major question here is whether we can estimate $E(Y_{0i} | D_i = 1)$ using $E(Y_{0i} | D = 0)$.

If $E(Y_{0i} | D = 1)$ and $E(Y_{0i} | D = 0)$ were equal, what we want to measure and what we observe would be the same making our impact evaluation a straight forward task. Impact would be the difference between the mean outcomes of program participants and the mean outcomes of non-participants of the outcome of interest, assuming the two are equal. In

non-experimental or observational data, such a naive and straightforward outcome cannot be predicted. Rather than offering a simple comparison of outcomes between the treatment group and the control group, impact evaluation examines the causal consequences of program participation (Pitt and Khanddker, 1998). As stated above, the question is how to estimate $E(Y_{0i} | D = 1)$ when Y_{0i} is not observed for those individuals with $D = 1$. We are thus left with the possibility of using the outcomes of non-treated individuals (control group) using which we can measure what treated individuals would have received had they not participated. The average treatment effect can also be written as follows (Wooldridge, 2002; Cobb-Clark and Crossley, 2003; Cameron and Trivedi, 2005):

$$E(Y_{1i} | D = 1) - (E(Y_{0i} | D = 0)) \\ = E(Y_{1i} - Y_{0i} | D = 1) + E(Y_{0i} | D = 1) + E(Y_{0i} | D = 0)$$

A simple comparison of the observed outcomes of those participating and those not participating in the program would yield biased estimates. And the bias is given by the difference between $E(Y_{0i} | D = 1)$ and $E(Y_{0i} | D = 0)$. The cause of the bias is the fact that $E(Y_{0i} | D = 1)$, which shows what would have happened to the outcome variable if the participants did not in fact participate in the program, is not directly observable. This is what is known as the counterfactual. Bias will be zero in the case of randomized program placement, however, in cases where treatment is not random such as when participants self select for treatment, we have bias due to selection (selection bias). The fact that the counterfactual mean is not directly observable makes the evaluation of impacts a difficult task. It is for this reason that impact evaluation is considered as a problem of missing data (Ravallion, 2001; Cobb-Clark and Crossley, 2003; Heckman et al., 1997).

The treatment selection bias is divided into two components by Ravallion (2001), the first being bias owing to differences in unobservable factors, and the second being bias due to differences in observable features. The former refers to unobservable elements such as borrowers' or non-borrowers' entrepreneurial ability or motivation, which result in a systematic relationship between program participation and outcome. The latter is due to a lack of relevant comparison groups or shared support between the treated and non-treated groups. This means that we aren't comparing likes against likes in terms of control variables like demographics.

We use matching estimating approaches to deal with the difficulties of missing data and selection bias mentioned above. Matching is a technique for reducing selection bias by estimating the counterfactual or unobserved outcome of program participants from the outcome of nonparticipants with similar visible qualities. It is based on the premise that the best estimate of the counterfactual result is to locate the best match in terms of observable features from the eligible control group. In this study, it means that we may estimate the counter group by comparing a household or households receiving row-seeding technology to those in the control group.

Propensity score matching constructs a statistical comparison group by matching observations within the program to non-participants on similar values of $P(x)$. Matching

estimators are developed based on the assumption of **conditional independence**. In a randomized program treatment, participation and outcome are known to be conditionally independent given control variables (X_i 's):

$$(Y_0, Y_1) \perp D \mid X$$

The assumption means that given X , one can use the counterfactual outcome in the treated groups as the same as the observed outcomes for the non-treated group. This implies that non-participant's outcomes (counterfactual) approximate the outcome level of participants had they not participated.

Using their assertion that 'treatment assignment is strongly ignorable', Rosenbaum and Rubin

(1983) displayed that, for non-randomized observations, outcome and treatment are conditionally independent given the propensity score, $P(x)$, which is the conditional probability of receiving treatment given pre-treatment characteristics. The implication of this assumption is for an individual with the same propensity score, $P(x)$; potential outcomes are independent of treatment assignment:

$$(Y_0, Y_1) \perp D \mid P(x)$$

A balancing condition needs to be satisfied for propensity score matching. The balancing condition shows the conditional independence of participation in terms of control variables given the propensity score:

$$D \perp X \mid P(x)$$

The balancing condition, on the other hand, states that treatment assignment is random for those with the same propensity score. If the balancing condition is met, observations with the same propensity score, regardless of treatment, will have the same distribution of observable and unobservable attributes. This means that treatment is virtually randomized with the use of the propensity score, and that treatment and control group members will be observationally identical on average (Becker and Ichino, 2002). The propensity score reduces the high dimensional matching problem in to one-dimensional problem provided that $p(x)$ is known (Heckman et al, 1997; Cobb-Clark and Crossley, 2003).

If the above two assumption are satisfied, then, after conditioning on P , the Y_0 distribution observed for the matched non-participant group can be substituted for the missing Y_0 distribution for participants. Under these assumptions, the mean impact of the program is given by:

$$\begin{aligned} ATT &= E(Y_1 \text{ or } C_1 - Y_0 \text{ or } C_0 \mid D_i = 1) \\ ATT &= E\{E(Y_1 \text{ or } C_1 - Y_0 \text{ or } C_0 \mid D_i = 1, P(x))\} \\ &= E\{E(Y_1 \text{ or } C_1 \mid D_i = 1, P(x)) - E(Y_0 \text{ or } C_0 \mid D_i = 0, P(x)) \mid D_i = 1\} \end{aligned}$$

The first term on the right hand side of the last expression can be estimated from the treatment group, while the second term can be estimated from the matched on (P) comparison groups' mean outcomes.

The propensity score, which reflects the likelihood of participation, is a continuous variable, and two or more observations with the same propensity score are very hard to find. As exact matching is difficult to achieve, the study relies on inexact matching techniques such as stratified matching, Nearest Neighbour Matching, Radius matching, and Kernel matching.

Results and Discussion

Demographic and socioeconomic characteristics of sample households

The study focuses on the demographic and socioeconomic characteristics of surveyed households in the study area. As a result, the average household size of sample households in the research area was above four people per household, which is higher than the national average. On average, each household has 1.5 hectares of land. Furthermore, the average tropical livestock holding at the household level is roughly 1.8, which is lower than mean TLU in other rural area of the country (Zewdie 2010, Yonas 2014). Farmers can produce an average of 13 quintal of Teff per hectare and can afford monthly consumption expenditures of roughly 224 ETB.

Impact of technology adoption on outcome variables

In terms of farm asset value, housing asset value, consumption expenditure, and agricultural output, there was a huge and positive difference between adopters and non-adopters. Households who employ row seeding technique have higher agricultural asset values than their non-user counterparts. The change is statistically significant and the direction is favourable. New technology has a favourable and significant impact on the home asset holdings of individuals. Row seeding technology Adopter households' home asset values are much higher than their non-adopter counterparts.

Table 1: Average TLU, asset holding and land holding of the household by participation

Outcome variables	Total	Participants	Non-participants	Mean Difference	t-value
Farm asset value (after adoption)	317.28	343.41	291.15	52.26	2.48**
Home asset value (after adoption)	486.89	719.18	254.59	464.59	6.81***
Livestock holding (after adoption)	2.33	3.30	1.36	1.94	1.49
Consumption expenditure (after adoption)	257.57	299.59	215.54	84.06	3.91***
Teff production per hectare (after adoption)	13.56	15.77	11.34	4.42	3.91***

Source: Compute from own Survey, 2013. ***= significance level at 1%, ** at 5% & * at 10%
 The primary purpose of deploying yield-increasing agricultural technology is to provide food security while also improving the welfare of rural households and society as a whole. As a result, row seeding technology applications have a considerable impact on a rural household's welfare indicator such as consumption expenditure as a proxy in this study. Adopters spent more money on consumption than non-adopters. Between adopters and non-adopters, there was a significant difference in welfare (consumption expenditure used as a proxy).

Row seeding technology has a remarkable impact on Teff productivity, according to the study. In terms of Teff output per hectare, there was a considerable difference between adopters and non-adopters. When compared to broadcasting procedures, row planting technology increased Teff per hectare productivity by 4.42 kuntal.

Generally, the use of row seeding technology had a good and considerable impact on household home asset, farm asset, consumer expenditure, and Teff production. Based on the three matching estimators with bootstrapped standard errors, this was shown to be statistically significant at less than 1% level of significance. Based on the three matching estimators with bootstrapped standard errors, the mean difference was statistically significant at less than 1% significance level.

Econometric Analysis of Impact of the adoption of Row seeding technology

The PSM technique was used to investigate the effect of row seeding techniques. As a result, a logistic regression model was used to estimate propensity scores, with the dependent variable being a binary variable indicating 1 for early adopter of new technology and 0 otherwise. The data was analysed using Stata version 13.1 software.

Impact on Livestock holdings: In terms of livestock holding, there was a significant disparity between adopters and non-adopters. TLU differences between technology users and nonusers were shown to be positive on average. Based on the radius matching estimators, this was shown to be statistically significant at less than 1% level of significance and to have a favourable effect on the other estimators, but not statistically significant.

Table 2: ATT estimation results of the impact of row-seeding technology adoption on livestock holding

Outcome variables	Matching algorithm	No. of adopter	No. of non-adopter	ATT	t-value
Livestock holding	Nearest Neighbor	100	55	1.882	1.445
	Stratification	100	99	1.933	1.486
	Radius	32	34	0.744	4.284***
	Kernel with robust	100	99	1.917	1.388
Livestock value	Nearest Neighbor	100	55	3261.030	6.518***
	Stratification	100	99	2993.986	7.286***
	Radius	32	34	3518.997	4.633***
	Kernel with robust	100	99	3142.167	7.852***

Source: Compute from own Survey, 2013. ***= significance level at 1%, ** at 5% & * at 10%
 The use of row planting procedures has a beneficial and statistically significant impact on livestock values. When compared to their non-user counterparts, users have more valuable livestock. Row seeding procedures, on the whole, have a large and good impact on both livestock units and their values. Regarding to the livestock values, all matching algorithm gives statistically significant at 1 % significance level.

Impact on farm and home assets

According to PSM estimates, the use of row planting technology has a considerable impact on agricultural asset and home asset holding. Adopters' agricultural and house assets were worth more than their non-adopter peers. On average, adopters' farm assets are worth 71.17 and 50 Ethiopian Birr more than non-adopters' on the basis of nearest neighbour, stratification, and Kern matching, respectively. Except for radius matching, the difference is statistically significant in all matching algorithms. In all matching algorithms, the mean difference is statistically significant at 1% in the case of home asset values and at 10% in the case of farm asset values.

Table 3: ATT estimation results of the impact of row-seeding technology adoption on asset holding

Outcome variables	Matching algorithm	No. of adopter	No. of non-adopter	ATT	t-value
Farm asset value	Nearest Neighbor	100	55	71.170	2.065*
	Stratification	100	99	52.046	2.459*
	Radius	32	34	18.783	0.393
	Kernel with robust	100	99	50.546	2.009*
Home asset value	Nearest Neighbor	100	55	445.370	6.079***
	Stratification	100	99	465.049	6.807***
	Radius	32	34	474.275	4.477***
	Kernel with robust	100	99	458.889	6.766***

Source: Compute from own Survey, 2013. ***= significance level at 1%, ** at 5% & * at 10% Adopter households' home asset values are higher than non-adopter households' asset values. There is a considerable disparity in all matching algorithms, with the mean difference above 400 Birr.

Impact on consumption expenditure and output of Teff

Government and non-governmental development agencies have consistently used agricultural output-boosting technology to promote individual and household food security. As a result of the implementation of row seeding practices, the welfare position of households improved, as evidenced by the estimation results. The results revealed that technology users produce much more than their non-user peers. In almost all matching algorithms, technology users outperform non-users in terms of productivity.

Table 4: ATT estimation results of the impact of row-seeding technology adoption on output of Teff and consumption expenditure

Outcome variables	Matching algorithm	No. of adopter	No. of non-adopter	ATT	t-value
Total expenditure per adult equivalent household size	Nearest Neighbor	100	55	67.789	2.602**
	Stratification	100	99	83.389	3.870***
	Radius	32	34	42.480	1.584
	Kernel with robust	100	99	80.285	4.087***
Total output of Teff per hectare	Nearest Neighbor	100	55	3.568	2.602**
	Stratification	100	99	4.389	3.870***
	Radius	32	34	2.236	1.584
	Kernel with robust	100	99	4.226	3.696***

Source: Compute from own Survey, 2013. ***= significance level at 1%, ** at 5% & * at 10%

In terms of realized welfare indicators such as consumer spending, users outperform non-users, and there is a significant difference in welfare between users and non-users. Users of row seeding technique have a higher standard of living than their non-user peers. The results of this study showed that program participants spent more money on food and total per adult equivalent consumption than non-participants.

Conclusion and recommendations

It was discovered that the involvement of the Row seeding technology adoption allowed participants to keep their assets. Participants in the technology adoption have grown their livestock holdings and have been able to protect (raise) their asset holdings as a result of the increasing return from agricultural crop production. According to the findings of this study, the mean difference in livestock holdings between adopter and non-adopter in terms of TLU was positive and significant. As a result, the government and non-governmental institutions should encourage the people to participate and utilize this technology which can in turn enhance the participation of people in commercialized dairy and fattening livestock development activities in order to reduce the problem of food insecurity and to improve their income sources.

In addition to productive assets, durable goods, and home items, the technology adoption has a favourable and statistically significant impact. The impact of the technology adoption on household consumption expenditure was also investigated in this study. The program enhanced the consumption expenditure of the participants. It has also positive and significant effect on output of cereal production. Thus, the development agents should continuously apply their effort to encourage the people to continue with this technology and scale up the practices for the non-user through providing training and field demonstration.

Moreover, the technology adoption has a remarkable significant effect on both farm and non-farm permanent home asset holdings. The finding reveals that program participants had a higher worth of farm asset (productive assets) at their current values than non-participants. The difference between program participants and non-participants in the mean value of productive assets was positive and significant. The implementation of row seeding technique had a favourable and statistically significant impact on the value of durable goods. This suggests that as a result of the program's assistance, program participants were able to protect their durable items. Therefore, the government should encourage the people to use row seeding technology that can enhance the asset holding of people which is very means of risk mitigation strategies.

According to the finding, the number of people who use row seeding technology is limited. As a result, development agents should encourage farmers to participate in row seeding

technology, as well as provide periodic follow-up and evaluation in order to maximize the technology's positive impact.

Reference

1. "Ethiopia – Overview". *World Food Programme*. 2010.
2. Abdulai. A, Tietje. H (2006) *Economic Reforms and Household Welfare in a Transition Economy: Evidence from Tajikistan, Department of Food Economics and Consumption Studies, University of Kiel, Olshausenstrasse 40, 24118 Kiel, German*
3. Becker Sascha O. and Andrea Ichino. (2002). "Estimation of average treatment effects based on propensity scores", *The Stata Journal*, Vol. 2, No. 4, pp. 358-377
4. Cameron. A. Colin, and Pravin K. Trivedi (2005). *Microeconometrics: Methods and Applications*, Cambridge University Press, Cambridge.
5. Cobb-Clark Deborah A., and Thomas Crossley. (2003). "Econometrics for Evaluations: An Introduction to Recent Developments", *The Economic Record*, Vol. 79, No. 247, PP. 491-511.
6. Dadi. L., M., Burton and A., Ozanne, (2004), *Durati on Analysis of Technology Adoption in Ethiopian Agriculture, Journal of Agricultural Economics*, 55-3: 613-631.
7. Dethier. J-jacques, Effenberger. A (2012). *Agriculture and development: A brief review of the literature*
8. Dorosh P. and Rashid S.(2012) *Introduction in Food and Agriculture in Ethiopia. Progress and Policy Challenges*
9. Endale K 2010: *Genetic Variability, Heritability, Correlation Coefficient and Path Analysis for Yield and Yield Related Traits in Upland Rice (Oryzasativa L.)*
10. Fufa. B, Behute. B, Simons. R, Berhe. T (2011). *Strengthening the Teff Value Chain in Ethiopia, Agricultural transformation agency*
11. Gilligan. D.O., Hoddinott,J. and Alemayehu, S. (2008). *An analysis of Ethiopia's Productive Safety Net Program and its linkages: International Food policy Research Institute, 2033 K Street, NW Washington, D.C. 20006.*
12. Heckman, J. J., Ichimura,H., and Todd, P. (1998). "Matching as an Econometric

13. Heckman, J.J., Ichimura, H. and Todd, P. (1997). *Matching as an econometric evaluation estimator: evidence from evaluating a job training programme, The Review of Economic Studies*, 64:605-654.
14. Kaluski DN, Ophir E, Amede T. 2001. *Food Security and Nutrition- the Ethiopian Case for Action, Public Health Nutrition* 5(3), 373-381
15. Kaluski DN, Ophir E, Tilahun A (2001). *Food security and nutrition – the Ethiopian case for action. Public Health Nutr.*, 5(3): 373-381
16. Mendola M, 2007: *Agricultural technology adoption and poverty reduction: A propensity-score matching analysis for rural Bangladesh*
17. Menmeru T (2014): *Population Growth and Cultivated Land in Rural Ethiopia: Land Use Dynamics, Access, Farm Size, and Fragmentation*
18. Mulugeta S, Sentayehu A, and Kassahun B, 2012: *Genetic Variability, Heritability, Correlation Coefficient and Path Analysis for Yield and Yield Related Traits in Upland Rice (Oryzasativa L.)*
19. Ravallion. M. (2001). *“The Mystery of the Vanishing Benefits: An Introduction to Impact Evaluation”, The World Bank Economic Review, Vol. 15, No. 1, PP. 115-140.*
20. Rosenbaum. P.R., and Rubin, D.B. (1983). *The Central Role of the Propensity Score in Observational Studies for Causal Effects. Biometrika*, 70 (1): 41-45.
21. Sanchez. P. A., G. L. Denning, and G. Nziguheba (2009). *The African Green Revolution Moves Forward. Food Security* 1:37-44.
22. *The impact of row planting of teff crop on rural Household income: A case of TahtayMaychewwareda, Tigray, Ethiopia By YonasBerh, 2014*
23. Wooldridge, Jeffrey M. (2002). *Econometric Analysis of Cross Section and Panel Data, the MIT Press, Cambridge, Massachusetts.*
24. *Zewude 2010: Livestock Production Systems In Relation With Feed Availability In The Highlands And Central Rift Valley Of Ethiopia, 2010*