The impact of agricultural technology adoption on income inequality: a propensity score matching analysis for rural Ethiopia

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Abstract: This study analyses the impact of agricultural technology adoption on income inequality. Primary data has been collected from 400 sample households in Awi zone of Ethiopia through household survey during agricultural season of 2017/18. The collected data were analysed by using propensity score matching method. The estimated results revealed that adoption of agricultural technologies such as chemical fertiliser and improved seeds significantly increase total household income but worsen income distribution. After adoption of agricultural technologies, income inequality measured by Gini coefficient increased ranged from 0.047 to 0.087. Hence, the government and other concerned authorities should exert more efforts in order to enhance technology adoption status of the poor households by increasing their accessibility for extension and credit services.

Keywords: technology adoption; income inequality; propensity score matching; Ethiopia.

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1 Introduction

It is believed that technological adoption significantly reduces poverty and improves the living standard of the society throughout the contemporary world mainly through increment in productivity. According to Mekonnen (2017), enhancing agricultural productivity improves the welfare of rural population by increasing food availability and reducing the price of agricultural outputs. Mendola (2007) also argues that adoption of agricultural technology reduces poverty by increasing farmers' productive capacity. Kassie et al. (2011) conclude that use of improved seeds raises income of farmers considerably and decreases rural poverty.

While green revolution has significantly increased productivity in many Asian and Latin America countries, in Africa, the level of adoption and its impact were not promising due to little interest shown by farmers for these technologies (Toborn, 2011). In this regard, Andersen and Hazell (1985) argued that in order to reap the benefits of green revolution, its implementation should be integrated into the country's development policies and programs and supported by appropriate institutions.

In Ethiopia, the agriculture sector has got a special attention in the development planning process of the government since the formulation of agricultural development led industrialisation (ADLI) strategy in 1993 (Khairo et al., 2005; Alemu et al., 2002). One of the main objectives of this strategy was modernising the Ethiopian agriculture through adoption and diffusion of new farm technologies (green revolution technologies) such as fertilisers and certified seeds. Moreover, successive national plans of the government such as Sustainable Development and Poverty Reduction Program (SDPRP), Plan for Accelerated and Sustainable Development to End Poverty (PASDEP) and Growth and Transformation Plans (GTP I and II) have given a strong emphasis on improving agricultural productivity through research-generated information and technologies, among others. Consequently, use of agricultural technologies such as improved seeds and chemical fertiliser has increased overtime though still falls short of the target set in order to transform small holder agriculture (MoFED, 2016)

There is growing consensus that assessments of economic performance should not focus solely on overall income growth, but also take into account income distribution (Hoeller et al., 2014). According to Warr and Coxhead (1992), a more equitable distribution of income is a major policy concern so that policy makers need to know the likely effects of technology adoption on the income of households.

Despite the fact that the effect of technology adoption on agricultural productivity is highly recognised, its effect on income inequality is far from clear. Some studies revealed that adoption of technology can worsen income distribution in which the improvement in income due to technology adoption benefited large-scale farmers than small-scale farmers (Freebairn, 1995; Sahoo, 2014; Huang et al., 2015). In contrary, some other studies revealed that the impact of technology adoption on increasing income is found to be better for smallholders than large farmers and hence reduces income inequality (Warr and Coxhead, 1992; Ut et al., 2000; Kilima et al., 2013; Matuschke et al., 2007; Becerril and Abdulai, 2010). On the other hand, Lin (1999) and Ding et al. (2011) conclude that the net impact of hybrid rice's adoption on income distribution is insignificant because of offsetting effect in production-mix adjustments and the existence of nearly the same rate of improved rice adoption between lower-income and large-income households.

From the literatures it is observed that even though improving agricultural productivity is considered as the most important strategy for improving the living standard of the people, the question of whether this change in income was fairly distributed among beneficiaries or not is far from clear. According to Todaro and Smith (2012), policy makers are worried about the distribution of income because extreme income inequality leads to economic inefficiency and undermines social stability and solidarity. Though, studying income distribution is very important, little is known about the impact of agricultural technologies on income inequality. Hence, the main objective of this study is to investigate the effect of agricultural technology adoption on income distribution based on survey data collected in Ethiopia.

The rest of the paper is organised as follows. The next section provides data and methods of estimation. In Section 3, results are presented and discussed. The last section provides conclusion and recommendations of the study.

2 Materials and methods

This study is carried out by using farm household survey during 2017/18 agriculture season. The survey was conducted in Awi zone of Ethiopia. In order to determine a representative sample size, Kothari (2004) formula has been employed and the appropriate sample size is estimated to be:

$$n = \frac{Z^2 \cdot p \cdot q \cdot N}{e^2(N-1) + Z^2 \cdot p \cdot q} = \frac{(1.96)^2 \cdot (0.5) \cdot (1-0.5) \cdot (204{,}370)}{(0.05)^2(204{,}370-1) + (1.96)^2 \cdot (0.5) \cdot (1-0.5)} \cong 400$$

where N is the total number of rural households in Awi Zone which was estimated to be 204,370 (CSA, 2015); p is the estimated proportion where 0.5 is usually considered; q represents $(1 - p)$; Z is the abscissa of the normal curve (1.96); and e is precision level (5% was considered).

In order to select samples from the population, multistage sampling procedure was employed. In the first stage, three out of eight districts were randomly selected; Banja, Guagusa-Shikudad and Guangua districts. At the second stage six kebeles[1] (two kebeles from each district) were randomly selected and at the third stage a total of 400 households were drown from the six kebeles randomly based on their population proportion.

2.1 Propensity score matching method

A direct comparison of adopters and non-adopters based on their level of income is misleading because the differences between them may not be resulted solely from the adoption of technologies but due to other socio-economic factors. Hence, the basic task here is to establish methods which can help to identify the true effect of technology adoption.

According to Blundell and Dias (2000), the choice of appropriate method depends on:

1 the type of information available to the researcher

2 the underlying model

3 the parameter of interest.

The most frequently used quasi-experimental design methods are propensity score matching (PSM), difference in differences, Heckman two-step selection approach and instrumental variables. However, Heckman two-step selection procedure and instrumental variables address the selection of unobservables by imposing distributional and functional form assumptions, such as linearity on the outcome equation and extrapolating over regions of no common support, where no similar adopter and non-adopter observations exist (Kassie et al., 2011) where as difference-in-differences method can be applied only when there exists repeated cross-sectional data (Blundell and Dias, 2000).

Hence, in this study, PSM was adopted to analyse the income inequality effect of agricultural technology adoption. The objective of PSM is to find the comparison group from a sample of non-adopters that is closest to the sample of adopters so as to get the impact of the technology on the beneficiaries.

PSM approach is a two-step procedure; the estimation of propensity scores followed by matching of adopters to non-adopters. In the first step, logit model was employed in order to compute the propensity scores for each observation.

When the dependent variable is dummy which takes either 1 (for something to be happened) or otherwise 0, most studies rely on either logit or probit models. These two models are quite similar and used interchangeably since there is no convincing reason to choose between them. In this paper logit model was applied due to its comparative mathematical simplicity (Gujarati, 2004). In this study the dependent variable is dichotomes or dummy in nature which take (1) for agricultural technologies adopter and (0) for non-adopter.

Propensity score is defined as the conditional probability of receiving a treatment given pretreatment characteristics (Rosenbaum and Rubin, 1983)

$$P(X) = \Pr(T = 1 | X) = E(T | X) \tag{1}$$

where $T = \{0, 1\}$ represents exposure to treatment and X is the multidimensional vector of pretreatment characteristics which include age, sex, education, family size, land size, distance from main market, access to credit, access to extension service and off-farm income.

The second step is estimation of the average treatment effect for the treated (ATT) following Rosenbaum and Rubin (1983).

$$ATT = E\left[Y^1 - Y^0 \left| P(X)\right.\right] = E\left[Y^1 \left| T = 1, P(X)\right.\right] - E\left[Y^0 \left| T = 0, P(X)\right.\right] \tag{2}$$

where $E[Y^1 \mid T = 1, P(X)]$ is the income for the treated (technology adopters) and $E[Y^0 \mid T = 0, P(X)]$ is the income for technology adopters had it not been adopted, representing a counterfactual income.

There are diverse methods of propensity score matching methods applied in literatures including nearest-neighbour matching (NNM), kernel-based matching (KBM), radius matching and stratification matching. In this study, the technological effect on households' income was estimated thorough the two most widely used techniques; NNM and KBM (Kassie et al., 2011; Mendola, 2007; Mekonnen, 2017).

To determine the effect of agricultural technology on income inequality, this paper employed the method employed by Ding et al. (2011) and Huang et al. (2015). Hence, the extent of income inequality with and without technology adoptions was compared which the variation indicates the impact of agricultural technology adoption on income inequality.

But it was not easy to know the income of agriculture technology adopters before they have adopted the technology. Hence, simulation method was employed. In order to estimate farm households' incomes without technology, it is started by estimating the effect of technology adoption on income of adopters. The effect of technology adoption on households' income which is the Average Treatment for the Treated (ATT) is computed based on PSM method discussed above.

Then the computed ATT of farmers' income is subtracted from the observable income of technology adopters so as to determine the counterfactual income. The observable income was used for non-adopters.

Finally, Gini coefficients were computed for the two scenarios independently. One based on the observable household income distributions and the other based on the counterfactual income distribution which the differences between them represents the impacts of technology on income inequality.

Moreover, to measure the contribution of each sources of income (crop income, livestock income and off-farm income) to the total income inequality, this study employed decomposition of the Gini coefficient as formulated by Pyatt et al. (1980).

The decomposition is as follows:

$$G = \sum_{K=1}^{K} W_K C_K = \sum_{K=1}^{K} S_K R_K G_K \tag{3}$$

where

S_K is the share of income from source K

C_K is the concentration ratio of income source K

$$C_K = R_K G_K$$

R_K is the rank correlation ratio for income source K

G_K is the Gini coefficient for income source K.

3 Results and discussion

3.1 Descriptive analysis

This section describes households' characteristics and other selected variables in relation to their behaviour of technology adoption. Hence, comparison is made between adopters and non adopters of chemical fertiliser and improved seeds based on selected variables. To check the existence of statistically significance difference between them t-test for continuous variables and chi-square tests for categorical variables were employed.

In this study, Out of the total of 400 sample households, 211 (52.75%) of farmers adopted chemical fertiliser and improved seeds in at least one of their crops during the agricultural season of 2017/18. This result is consistent with recent studies in Ethiopia such as Abate et al. (2016) and Husen et al. (2017) while adoption rates of this study were found to be better than other earlier studies (Asfaw et al., 2011; Beshir et al., 2012). Hence, it validates that adoption of fertilisers and improved seeds in Ethiopia have increased over time (Shita et al., 2018).

Table 1 summary of variables by adoption status

Variables		*Non-adopters (n = 189)*	*Adopters (n = 211)*	*t-stat/chi-square*
Age of household head		47.4709	44.62085	2.4087**
Family size		5.730159	6.729858	-5.3629***
Land size (hectare)		1.084344	1.194289	-1.8235*
Off farm income (Birr)[a]		4,872.222	4,233.033	1.1831
Distance to the main market (km)		6.375132	6.37346	0.0063
Sex of household head	Male	45.23%	54.77%	7.2711***
	Female	69.70%	30.30%	
Education level of household head	Illiterate	54.22%	45.78%	12.9125***
	Primary	36.22%	63.78%	
	Secondary	33.33%	66.67%	
Access to credit	Yes	29.09%	70.91%	64.6806***
	No	69.44%	30.56%	
Access to extension service	Yes	38.25%	61.75%	21.9127***
	No	62.42%	37.58%	

Notes: [a]Birr is the unit of currency in Ethiopia (1 birr = 0.035 USD on 06/12/2018).
*, **, *** significance level at 10%, 5% and 1% , respectively.

Source: Authors' field survey (2018)

As it is indicated in Table 1, agricultural technology adoption rate of male headed households was better than females. The average age of adopters was found to be lower than non-adopters, implying that as age increases adoption of agricultural technologies will decline. The result indicates that the average family size of technology adopter households were greater than non-adopters. Compared to non-adopters, adopters' level of education was found to be better; the proportion of households who attended primary and secondary education is relatively better than non-adopters. In Ethiopia, land is the most important factor of production and sources of income since more than 80% of the population lives in rural area. In this regard, the average landholding size of technology adopters was greater than non-adopters with 10% level of significance, 1.19 and 1.08 hectare respectively. Concerning institutional factors, adopters had better access of extension and credit services than non-adopters.

Table 2 indicates the difference in income among adopters and non-adopters. It revealed that the total income of households who adopted agricultural technologies (fertiliser and improved seeds) was more than non-adopters by 16,445.03 birr. The gap in total income is primarily resulted from the difference in crop income followed by livestock income. However, there is no statistically significant difference in off-farm between the two groups.

Table 2 Income of households by sources and adoption status

Sources of income	*Adopters*	*Non-adopters*	*Difference*	*t-test*
Crop income	30,111.5	18,298.74	–11,812.76	–3.8870***
Livestock income	13,903.78	8,632.331	–5,271.451	–6.0670***
Off-farm income	4,233.033	4,872.222	639.189	1.1831
Total	48,248.32	31,803.29	–16,445.03	–5.1535***

Note: *** indicate 1% level of significance.

Source: Authors' field survey (2018)

Table 3 reports Gini coefficients of total household income and its components. The Gini coefficient of total household income was estimated to be 0.269. The result is not far from the national average Gini coefficient for Ethiopian rural households. In 2015/16, Gini Coefficient measured by the income (consumption) inequality in Ethiopia was found to be 0.284 for rural households (MoFED, 2017). Similarly, a study by Gatiso and Wossen (2015) estimated the aggregate income Gini coefficient in rural Ethiopia to be 0.274. In line with the result of this study, the Gini coefficient based reports of UNDP grouped Ethiopia as a country with very low income inequality (UNDP, 2016).

As indicated in Table 3, crop income is the major source of income for rural farmers which accounts for 60.6% of their total income. Livestock income comprises the second largest sources of income which was 28.8%. However, off-farm income contributes only 11.2% which is the lowest among other sources of income.

Table 3 Gini coefficients by income components

Source of income	*Sk*	*Gk*	*Rk*	*Share*	*% change*
Crop income	0.6060	0.3671	0.8382	0.6920	0.0860
Livestock income	0.2820	0.4165	0.6008	0.2619	–0.0201
Off-farm income	0.1120	0.6167	0.1797	0.0461	–0.0659
Total income	1.0000	0.2695	1.0000	1.0000	0.0000

Source: Authors' field survey (2018)

As reported in colum 3 of Table 3, off-farm income is the most unequally distributed (G_k = 0.6167) source of income followed by livestock income (G_k = 0.4165). Relatively crop income is the most equally distributed income source (G_k = 0.3671). However, crop income contributes the largest share in income inequality (69.2%) followed by livestock income (26.19%). The share of off-farm income to total income inequality was appeared to be the lowest with only 4.61%.

Moreover, column 6 presents the elasticity of Gini for each sources of income. Crop income is found to be an inequality increasing source of income (8.6%). In contrary, off-farm income was the main inequality decreasing sources of income with elasticity of –6.59%. The reason may be due to larger participation of the poor in off-farm activities.

3.2 Econometric results

As explained above, logit model was used to estimate the propensity scores of technology adoption for each observation where the dependent variable (technology adoption) takes the value of 1 if a farmer adopts at least one type of improved seed and one type of chemical fertiliser simultaneously and 0 otherwise. The result is reported in table 4. Goodness of fit measures confirmed the soundness of the logit model. The likelihood ratio test statistics indicating that the hypothesis of all coefficients are equal to zero is rejected at 1% level of significance. Moreover, the logit estimates of the adoption equation correctly predict 79.15% adopters and 68.25% of non-adopters which altogether had 74% correctly classified observations.

Table 4 Logit regression result

Variable		*Coefficient estimates*	
Age		–0.026 (0.011)**	
Sex (female = 0)		0.503 (0.496)	
Education level (illiterate = 0)			
Primary		0.549 (0.262)**	
Secondary		1.05 (0.533)**	
Family size		0.367 (0.071)***	
Access to extension service (no access = 0)		0.717 (0.254)***	
Access to credit (no = 0)		1.684 (0.245)***	
Distance from the main market		–0.056 (0.049)	
Land holding size		0.200 (0.207)	
Off-farm income		–0.00002 (0.00002)	
Constant		–2.827 (0.886)***	
Number of observations		400	
Pseudo R^2	0.225	Sensitivity	79.15%
Log-likelihood	–214.199	Specificity	68.25%
LR chi-square (p-value)	124.91 (0.000)	Correctly classified	74.00%

Notes: Standard errors are reported in parentheses.
** and *** indicate significance at 5% and 1% levels, respectively.

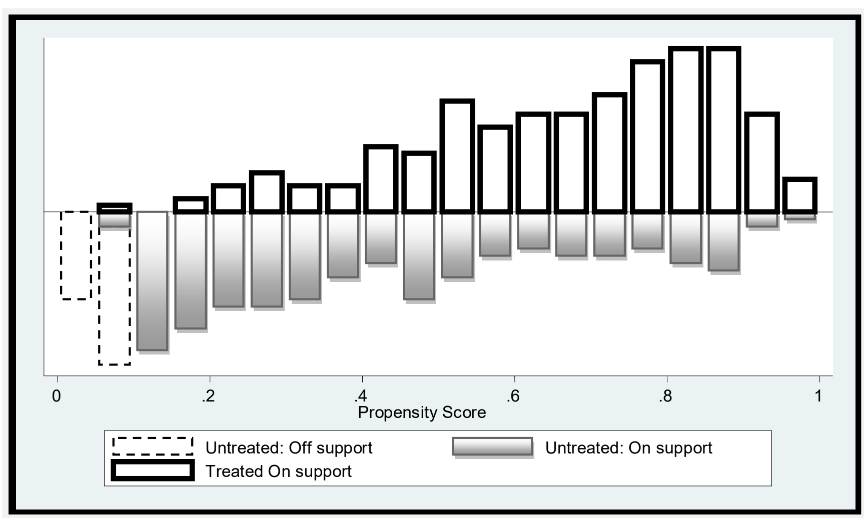
Source: Authors' field survey (2018)

The results indicate that adoption of agricultural technologies is influenced positively and significantly by number of family sizes, level of education, accessibility of extension service and credit. The existence of large family members in a household increases technology adoption since adoption of technology requires more labour for farming activities such as cultivation, planting and weeding than non-adopters (Asfaw et al., 2011; Birthal et al., 2012; Adofu et al., 2013). Education promotes awareness about the possible advantages of agriculture technologies that can enhance its adoption (Adeoti, 2009; Kassie et al., 2011). Access to extension service may increase technology adoption by enhancing farmers' awareness towards the importance and practice of new technologies (Gebregziabher et al., 2014; Husen et al., 2017). Promoting accessibility of credit for households' enhances the rate of technology adoption since accessibility of credit reduces the problem of capital shortages in order to the purchase improved technologies at the right time (Gebregziabher et al., 2014; Abate et al., 2016).

In contrast, as age of the household head increases, adoption reduces. This may be due to the fact that relatively aged farmers might be more reluctant and conservative towards adoption of agricultural technologies (Hailu et al., 2014).

After the estimated logit model, propensity scores were predictable for each household. The results of the predicted propensity scores suggested the region of common support of [0.09280763, 0.98548041] where only 31 (7.75%) out of 400 observations were out of the common support. As it is indicated in figure 1, the common support condition was satisfied since there exists considerable overlap in the distribution of the propensity scores of both adopter and non-adopter groups.

Figure 1 Propensity score distribution and common support (see online version for colours)



Source: Authors' field survey (2018)

Before the estimation of the impact of technology adoption, quality of alternative matching algorithms were checked based on mean standardised bias, pseudo R^2 and likelihood ratio tests before and after matching. As it is shown in Table 5, the mean standardised bias was 31.5% before matching and it is reduced to 7.0% to 6.4% with a substantial reduction in standardised bias ranged from 77.8% to 79.7%. The pseudo R^2 was 22.5% before matching and reduced ranging from 1.0–1.4%. Moreover, the likelihood ratio tests show the joint insignificance of covariates after matching while it was significant before matching. Hence, low mean standardised bias, high total reduction of bias, low pseudo R^2, and insignificant p-values of the likelihood ratio test after matching recommend that the PSM procedure is reasonably successful.

Table 5 Covariate balance indicators before and after matching

Matching algorithm	*NNM-1*	*NNM-5*	*KBM-0.03*	*KBM-0.06*
Mean std. bias (before)	31.5	31.5	31.5	31.5
Mean std. bias (after)	6.5	6.4	7.0	7.0
Percentage of bias reduction	79.4%	79.7%	77.8%	77.8%
Pseudo R^2 (before)	0.225	0.225	0.225	0.225
Pseudo R^2 (after)	0.014	0.011	0.012	0.010
LR χ^2 with p-value (before)	124.71 (0.000)	124.71 (0.000)	124.71 (0.000)	124.71 (0.000)
LR χ^2 with p-value (after)	7.77 (0.651)	5.22 (0.876)	5.62 (0.846)	4.98 (0.892)

Notes: NNM-1: Nearest neighbor matching with single neighbours.
NNM-5: Nearest neighbor matching with five neighbours.
KBM-0.03: Kernel based matching with 0.03 bandwidth.
KBM-0.06: kernel based matching with 0.06 bandwidth.

Source: Authors' field survey (2018)

The effect of fertiliser and improved seed utilisation on households' income is estimated after checking of matching quality of different algorithms. The result is reported in Table 6.

Table 6 Impact of agricultural technology adoption on households' income

Matching algorithm	*ATT*	*Std. err.*	*t-stat*
NNM-1	11,293.29	3,558.64	3.17***
NNM-5	13,543.10	3,869.60	3.50***
KBM-0.03	13,667.47	3,882.95	3.52***
KBM-0.06	13,238.83	3,612.44	3.66***

Note: *** indicates 1% level of significance.

Source: Authors' field survey (2018)

The estimated ATT revealed that adoption of chemical fertiliser and improved seeds resulted in a positive and significant effect on households' income. The income of technology adopters was higher than non-adopters ranged from 11,293.29 birr to 13,667.47 birr based on alternative matching algorithms. The result is consistent to many similar studies which conclude that adoption technologies improves the income of households by enhancing agricultural productivity (Kassie et al., 2011; Huang et al., 2015; Lin, 1999)

Finally, the effect of agricultural technology on income inequality was estimated and presented in table 7. The estimated Gini coefficients on observed income (with technology adoption) and the counterfactual income (without technology adoption) based on different PSM algorithms are presented. It is found that adoption of chemical fertiliser and improved seeds resulted in widening of income distribution. Gini coefficients increased ranged from 0.047 to 0.087. This result may not be surprising because as it is shown in the previous discussions, technology adoption resulted in a significant increase in total income and crop income was found to be the main income inequality increasing source of income which is directly affected by technology adoption. Hence, this finding may lead us to the conclusion that adoption of agricultural technologies increases income inequality in which the income resulted from agricultural technology adoption was unequally distributed implying that higher-income farmers benefited more than small-income (Freebairn, 1995; Sahoo, 2014; Huang et al., 2015). In contrary to Lin (1999) finding, in this study even though livestock income and off-farm income were found as inequality decreasing sources of income their effect was small since their contribution in the total income was small.

Table 7 The impact of agricultural technology adoption on income inequality

Matching algorithm	*Gini coefficient (with technology)*	*Gini coefficient (without technology)*	*Difference*
NNM-1	0.269	0.222	0.047
NNM-5	0.269	0.197	0.072
KBM-0.03	0.269	0.202	0.067
KBM-0.06	0.269	0.182	0.087

Source: Authors' field survey (2018)

4 Conclusions

This study analysed the impact of agricultural technology on income distribution by using propensity score matching model. For the purpose, data were collected from 400 farm households from three districts in Awi zone, Ethiopia. The study found significant and positive impact of agricultural technology on the income of households. However, it simultaneously worsen distribution of income implying that large farmers were more benefited from adoption that the poor. Hence, the policy implication here is that efforts to promote adoption of agricultural technology should be enhanced. But at the same time proper measures should be taken to distribute the benefits of technologies proportionately for the farm households. Hence, the government and other concerned authorities should focus on improving adoption of technologies by the small (poor) households through provision of formal education, increasing their accessibility for extension and credit services.

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Notes

1 Kebele is the smallest administrative unit of Ethiopia which consists of at least 500 households, or the equivalent of 3,500 to 4,000 persons.