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Impacts of Adopting Improved Barley Varieties on Farmers' Income in Ethiopia

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ABSTRACT

Improved agricultural technology adoption is vital in enhancing production, productivity, food security, and poverty reduction. This study assessed the level of income improvement as the result of adopting improved barley varieties for smallholder barley producers in Ethiopia. A multi-stage sampling method was followed to randomly select 18 districts, 42 kebeles, and 626 sample households from the potential barley-producing regions of Ethiopia, namely the Oromia, the Amhara, and the SNNP regions. The propensity score matching was estimated using logistic regression, and the kernel matching with a bandwidth of 0.1 was utilized to match 220 adopters with 402 non-adopters by rejecting two observations from adopters, and two observations from non-adopters. Finally, the treatment effect was estimated, and the result confirmed that farm households who adopted improved barley varieties got an extra income of birr 13,174.51 compared to non-adopter households. Therefore, agricultural policies and strategies in favor of the generation, dissemination, and adoption of improved farm technologies are recommended to take the lives of millions out of poverty and food insecurity.

INTRODUCTION

Over the past six decades, the world's agriculture sector has radically transformed. This sector has been the primary source of employment, food security, and income in most Sub-Saharan countries. However, the sector's productivity lagged behind the rest of the world due to several reasons like low investment in agricultural research and development, limited access to improved agricultural technologies, low market access to both agricultural inputs and outputs, and weak agricultural extension systems (Fuglie *et al.*, 2024).

Barley is the fourth most important cereal crop in terms of acreage and total production across the globe next to wheat, corn, and rice (Tricase *et al.*, 2018). It is the most widely grown crop in the world, with a cultivated land area of 47,2 million hectares and an annual production of 154.9 million tons in 2022. Russia, Germany, France, and Canada are the world's largest barley producers, with an annual production of 17.5, 11.4, 10.6, and 10.4 million tons, respectively. Ethiopia is the largest Barley producer in Africa with an annual production of 2,4 million tons followed by Algeria and Morocco whose annual production amounted to 1.6 million and 696,379.8 tons respectively (FAOSTAT, 2024).

In Ethiopia, barley is the most important food crop being cultivated by more than 3.6 million smallholders. It is the 5th most important cereal crop in terms of total production next to maize, wheat, tef, and sorghum. It is also the 5th cereal crop in terms of acreage following tef, maize, wheat, and sorghum during the main production season of 2021/2022. The crop was cultivated on 799,127.8 hectares, and a total production of 2.1 million tons was harvested. Regionally, more than 99 % of both the total production and the land allocated to the crop comes from the Oromia, Amhara, and the SNNP regions. Oromia region accounts for 60 % of the total production and 54 % of the total land allocated to barley production. The Amhara region also accounts for 31 % of the total production and 36 % of the land allocated to barley. (ESS, 2022).

The national average productivity of the crop is 2.6 tons/hectare, which is below the potential of the nationally released varieties, and that of the world's average. During the last 20 years, the government of Ethiopia has been implementing different agricultural policies and strategies intended to improve the production and productivity of smallholders. Development and utilization of high-yielding and disease-resistant varieties were among the main focus of the policy to improve production and productivity (Mengistu *et al.*, 2017).

Development, dissemination, and adoption of improved agricultural varieties were confirmed to have a significant effect in improving production, productivity, income, welfare, and food security, and in reducing the yield gap, poverty, and food price through enabling marketable surplus production in developing countries (Bahta *et al.*, 2018; Biru *et al.*, 2020; Gadisa & Addisu, 2022; Houeninvo *et al.*, 2020; Khonje *et al.*, 2015; Makate *et al.*, 2017; Tesfaye *et al.*, 2016; Wake & Habteyesus, 2019; Wordofa *et al.*, 2021).

However, to the best knowledge of the researchers, no comprehensive studies are exploring the impacts of adopting improved barley varieties on household income at the national level. Therefore, this study was designed to assess the impacts of adopting improved barley varieties on household income in Ethiopia using the primary data collected from major barley-producing areas of the country.

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MATERIALS AND METHODS

Data and the Study Area

Primary data was collected from 626 barley producers randomly selected across major barley-producing regions of Ethiopia. A multi-stage random sampling technique was followed to pick the required representative sample households. The three major barley-producing regions, the Oromia, the Amhara, and the SNNP regions were purposively selected based on their potential in barley production. These three regions account for more than 99 % of the national barley production. Then 5 zones from the Oromia region, 1 zone from the Amhara region, and 1 zone from the SNNP region were randomly selected from the potential barley-producing zones of the respective regions. In the third stage, 12 districts from Oromia, 4 districts from Amhara, and 2 districts from the southern region, a total of 18 districts were randomly selected. Then 24 kebeles from Oromia, 12 kebeles from Amhara, and 6 kebeles from SNNP, a total of 42 kebeles were randomly selected. Lastly, 15 sample households from each kebele, a total of 630 sample households, were selected and interviewed. However, 4 observations were discarded for incomplete information. Out of the complete observations, 222 (35.5%) were adopters, and the rest 404 (64.5%) were non-adopters. The secondary data used in this research were collected from published and unpublished sources.

Method of Data Analysis

Descriptive, inferential, and econometric data analyses were executed. Mean, minimum, maximum, and standard deviation were used to summarize the included socio-economic, institutional, and demographic variables. Chi-square and t-tests were used to check for the presence of significant differences between adopters and non-adopters based on the variables included. For the impact assessment, a propensity score matching model (PSM) was employed to estimate the propensity score that we base on to match adopters and non-adopters for assessing the average treatment effect (ATT).

Analytical Framework

The Propensity Score Matching (PSM) was the preferred method to estimate the propensity score based on the nature of the data. PSM is the statistical technique used to create a comparison group for treatment and control groups based on the propensity scores, which represent the conditional probability of receiving the treatment given a set of observed covariates. As stated by Rosenbaum and Rubin, if the potential outcomes of the control and the treatment are independent of the treatment allocation conditional on the observed covariates, then they are also independent of the treatment conditional on the estimated propensity scores (Rosenbaum & Rubin, 1985). Propensity score matching (PSM) implementation has five steps. These steps are the estimation of the propensity score, choosing the matching algorithm, restricting the common support region, checking the matching quality and estimation of the treatment effect, and sensitivity analysis respectively (Caliendo & Kopeinig, 2005).

For the estimation of the propensity scores, different statistical models can be used. The logistic regression model is the most frequently used method, we utilized it in this specific research. The functional form of the propensity score estimation can be expressed as:

$$P\,(D = 1 \mid X) = P(X) \tag{1}$$

Therefore, from Equation 1, the treatment effect for the observation i can be estimated as:

$$\tau_i = Y_i\,(1) - Y_i\,(0) \tag{2}$$

However, the fundamental problem here is only one of the potential outcomes is observable for the observation i, and the unobserved outcome is called the counterfactual. Hence, the estimation of the treatment effect for the individual is not possible, and focusing on the population average treatment effect is mandatory (Caliendo & Kopeinig, 2005).

Therefore, if we get the propensity score values for both the treatment and the control group from equation 1 if the assumption of the confoundedness holds, and if there will be sufficient common support regions for the treatment and the control group, the average treatment effect on the treated (ATT) can be estimated as:

$$\tau_{ATT} = E(\tau \mid D=1) - E[Y(0) \mid D = 0] \tag{3}$$

The matching quality of the model was assessed using different techniques like the covariate balancing tests, the number of observations included in the matching process, the t-test for the covariates before and after matching, and the joint significance test that comprises the standard bias and the pseudo-R^2 (Rosenbaum & Rubin, 1985). The value of the pseudo-R^2 indicates how well the regressors explain the probability of participation. If there is no systematic difference in the distribution of covariates after matching, the value of the pseudo-R^2 should be fairly low. Moreover, the value of the standard bias ranging from 3% to 5% is perceived to be good and if these conditions hold, the estimated ATT will be the pure effect of the treatment. Concerning the t-test, differences are expected before matching, while no significant difference is expected after matching (Caliendo & Kopeinig, 2005; Rosenbaum & Rubin, 1985; Sianesi, 2004).

RESULTS AND DISCUSSION

Descriptive Results

The result in Table 1 describes the summary of dummy variables included in the model. The result confirmed that access to credit services, off-farm income, access to extension services, and access to crop-specific vocational training were the variables positively and significantly related to farm households' decision to adopt improved barley varieties. This implies that household heads having access to credit, extension, off-farm, and training are more likely to adopt the varieties.

Table 1: Descriptive and inferential statistics results of dummy variables

Variables		Adoption of barley			χ2
		No	**Yes**	**Total**	
Sex of the household head	Female	39	15	54	0.2168
	Male	365	207	572	
Access to credit services	No	273	132	405	0.0421 **
	Yes	131	90	221	
Access to off-farm income	No	282	135	417	0.0225 **
	Yes	122	87	209	
Access to extension contact	No	44	13	57	0.0362 **
	Yes	360	209	569	
Crop disease occurrences	No	86	45	131	0.7648
	Yes	318	177	495	
Access to training on barley	No	286	116	402	0.0000 ***
	Yes	118	106	224	

*Source: Authors' survey results, ** and *** indicate the significance levels at 5 and 1%*

The result in Table 2 depicts that barley producers in Ethiopia earn a yearly income of birr 50,026.84 per year on average with a standard deviation of 50,847.04 from barley farming. The average income for adopters was 59215.65 birrs, and that of non-adopters was 44977.54 birrs with the standard deviations of 53793.41 and 48483.94 respectively. The higher values of the standard deviation both for the adopter and non-adopter indicate that the diversity across the barley farmers was very high, as the annual production ranged from 130kg to 9000 kg. Likewise, the standard deviation for the barley plot size was larger than the mean barley plot size as the result of the diversity across the barley farmers in terms of acreage allotted to barley farming that ranged from 0.061 to 6 hectares.

Table 2: Descriptive and inferential results of continuous variables

Variable	Adopters (222)		Non-adopters (404)		Combined (626)		t-test
	Mean	**St.dev.**	**Mean**	**St.dev**	**Mean**	**St.dev**	
Barley yield	1897.04	1733.05	1416.19	1576.97	1586.71	1648.80	3.52 ***
Livestock owned	8.32	3.97	8.30	3.96	8.30	3.96	0.07
Age of the head	47.08	12.78	47.92	12.52	47.62	12.61	0.80
Market distance	54.47	29.84	56.85	35.51	56.01	33.60	0.85
Barley plot size	0.38	0.56	0.25	0.50	0.21	0.52	0.71
Family size	6.05	2.23	6.04	2.25	6.04	2.24	0.00
Price of seed	32.23	6.87	32.30	7.39	32.27	7.20	0.12
Land owned	0.95	1.41	0.56	1.13	0.50	1.24	2.08 **
Education	1.54	0.68	1.53	0.79	1.53	0.75	0.21
Barley income	59215.65	53793.41	44977.54	48483.94	50026.84	50847.04	3.38 ***

*Source: Authors' survey results, ** and *** indicate the significance levels at 5 and 1%*

Econometric Results

Estimation of the Propensity Score

Estimation of the propensity score was done by regressing fifteen independent variables on the dependent variable (income from barley farming) using the logistic regression and the result is presented in Table 3. Before running the regression, the association between the variables, and the multicollinearity tests were done using the contingency coefficient, and the variance inflation factor (VIF), and the result confirmed that there was no problem.

Table 3: Estimation of the propensity scores

Variables	Coefficients	Standard error	P>z	Sig.
Sex of the head	0.205	0.329	0.533	
Age of the head	-0.007	0.008	0.336	

Education of the head	0.039	0.118	0.743	
Family size	-0.009	0.040	0.816	
Livestock owned	0.013	0.022	0.555	
Barley plot size	0.098	0.166	0.556	
Market distance	-0.002	0.003	0.562	
Off-farm income	0.377	0.185	0.042	**
Extension access	0.686	0.341	0.044	**
Credit access	0.447	0.183	0.014	**
Land owned	0.139	0.071	0.051	*
Training on barley	0.779	0.181	0.000	***
Cultivated land	0.005	0.011	0.667	
Seed price	0.005	0.012	0.659	
Crop disease	0.004	0.218	0.984	
_cons	-2.228	0.851	0.009	***
Logistic regression			LR chi2(15)	41.71
Number of observations	626		Prob > chi2	0.0002
Log-likelihood	-386.21		Pseudo R2	0.0512

*Source: Authors' survey results, *, **, and *** indicate the significance levels at 10, 5, and 1 % respectively*

The estimated propensity score ranged from 0. 1032416 to 0. 7914672 for the population with an average score of 0.3546326. But it ranged from 0. 1394752 to 0. 7914672 with a mean score of 0. 3979091 for adopters. Similarly, the propensity score for the non-adopters ranged from 0. 1032416 to 0. 7130161 with an average score of 0. 3308519. The summary of the propensity score for adopters, non-adopters, and the entire sample is presented in Table 4.

Table 4: Summary of the propensity scores for adopters, non-adopters, and the entire sample

Variable	Obs.	Mean	Std. Dev.	Minimum	Maximum
P-score (Non-adopters)	404	. 3308519	. 1099746	. 1032416	. 7130161
P-score (Adopters)	222	. 3979091	. 1331739	. 1394752	. 7914672
P-score (Combined)	626	. 3546326	. 1228840	. 1032416	. 7914672

Source: Authors' survey results

Choosing the Matching Algorithm

The matching quality of different algorithms like the nearest neighbor matching, radius matching, caliper matching, and kernel matching methods were tested as presented in Table 5. The matching algorithm with a larger number of matched samples, whose pseudo-r-square is the lowest, and can balance a maximum number of variables is considered the best matching method. Based on these, the kernel matching with a bandwidth of 0.1 was chosen for its quality of matching 622 observations out of 626, for its lowest pseudo-r-square value of 0.002, and for its ability to balance all (15) variables.

Table 5: Choosing the best matching algorithm

Matching Methods	Matched sample	Balanced variable	Pseudo R^2
The Nearest Neighbor Matching			
Nearest Neighbor (1)	622	14	0.017
Nearest Neighbor (2)	622	15	0.013
Nearest Neighbor (3)	622	15	0.009
Nearest Neighbor (4)	622	15	0.004
Caliper Matching			
Caliper (0.01)	402	14	0.046
Caliper (0.10)	420	13	0.119
Caliper (0.25)	426	13	0.166

Caliper (0.50)	440	13	0.147
Radius Matching			
Radius caliper (0.01)	617	15	0.003
Radius caliper (0.10)	622	15	0.006
Radius caliper (0.25)	622	14	0.038
Radius caliper (0.50)	622	12	0.051
Kernel Matching			
Kernel bandwidth (0.01)	617	15	0.003
Kernel bandwidth (0.10)	622	15	0.002
Kernel bandwidth (0.25)	622	14	0.026
Kernel bandwidth (0.50)	622	13	0.048

Source: Authors' survey results

Restricting the Common Support Region

The common support region is the propensity score value found between the maximum of the minimum propensity scores for both the treatment and the control, and the minimum of the maximum propensity scores of both the treatment and the control group. Therefore, from Tables 4 & 6, the common support region will be the values of the propensity scores found between 0.1394752 and 0. 7130161. The common support and the off-support region presented in Table 6 show that 4 observations, 2 from the treatment group and 2 from the control group failed in the off-support region, where 222 observations from adopters and 404 observations from non-adopters failed in the on-support region.

Table 6: Choosing the best matching algorithm

Adoption Status	Estimated propensity score		Common Support Region		
	Minimum	Maximum	Off-support	On support	Total
Adopters (222)	. 1394752	. 7914672	2	220	222
Non-adopters (404)	. 1032416	. 7130161	2	402	404

Source: Authors' survey results

Assessing the Matching Qualities

The covariate balancing test and estimation of the treatment effect were done under this sub-topic. The covariate balancing test results in Table 7 show that all the included variables become non-significant after matching.

Table 7: Covariate balancing test before and after matching

Variable	Unmatched	Mean		%bias	%reduce |bias|	t-test		V (T) / V(C)
	Matched	Treated	Control			t	P > |t|	
Sex of the head	U	0.93	0.90	10.60		1.23	0.22	.
	M	0.93	0.93	-0.30	97.10	-0.03	0.97	.
Age of the head	U	47.08	47.92	-6.60		-0.80	0.43	1.04
	M	47.00	47.05	-0.40	94.50	-0.04	0.97	1.02
Education	U	1.54	1.53	1.80		0.21	0.83	0.72*
	M	1.55	1.55	-0.40	78.50	-0.04	0.97	0.74*
Family size	U	6.05	6.04	0.00		0.00	1.00	0.99
	M	6.04	6.01	1.20	-5393	0.12	0.90	0.96
Livestock owned	U	8.32	8.30	0.50		0.07	0.95	1.01
	M	8.30	8.29	0.30	37.60	0.03	0.97	0.93
Barley plot size	U	0.62	0.59	5.80		0.71	0.48	1.26
	M	0.62	0.61	2.40	58.70	0.25	0.80	1.27
Market distance	U	54.81	55.62	-2.50	65.90	-0.26	0.80	0.69*
	M	0.39	0.38	0.60	97.00	0.06	0.95	.
Off-farm income	U	0.94	0.89	18.20		2.10	0.04	.
	M	0.94	0.94	-0.30	98.60	-0.03	0.98	.

Extension access	U	0.41	0.32	16.90		2.04	0.04	.
	M	0.40	0.38	4.80	71.40	0.50	0.62	.
Credit access	U	1.62	1.41	16.80		2.08	0.04	1.56*
	M	1.57	1.52	3.60	78.30	0.39	0.70	1.16
Land owned	U	0.48	0.29	38.70		4.70	0.00	.
	M	0.47	0.46	3.40	91.20	0.34	0.73	.
Training on barley	U	18.85	18.73	1.40		0.16	0.87	1.12
	M	18.79	18.48	3.70	-169.9	0.39	0.70	1.18
Barley seed price	U	32.23	32.30	-1.00		-0.12	0.90	0.87
	M	32.25	32.34	-1.30	-24.9	-0.13	0.89	0.84
Crop disease	U	0.80	0.79	2.50		0.30	0.77	.
		0.80	0.81	-2.40	5.400	-0.25	0.80	.

*Source: Authors' survey result, * if variance ratio outside [0.77; 1.30] for U and [0.77; 1.30] for M*

The joint significance test result of the covariate balancing test presented in Table 8 also confirms the matching quality of the model. The pseudo-r-square is 0.002 after matching while it was 0.051 before matching. The mean standard bias became 1.8 percent after matching while it was 8.9 before matching. The likelihood ratio also became non-significant after matching while it was significant at 1% before matching. Therefore, it will be reasonable to do the estimation of the average treatment effect on the treated (ATT).

Table 8: Joint significance test for covariate balancing before and after matching

Sample	Ps R2	LR chi2	p>chi2	Mean Bias	Med. Bias	B	R	%Var
Unmatched	0.051	41.38	0.000	9.8	6.6	54.1*	1.32	33
Matched	0.002	0.96	1.000	1.8	1.3	9.3	1.52	22

*Source: Authors' survey result, * indicates B>25%, and R outside of [0.5; 2]*

The ATT result presented in Table 9 confirms that the adoption of improved barley varieties has a positive and significant impact on the farm household's income. Adopters of improved barley varieties earn more annual income of birr 13,174.5 compared to non-adopters. This result is statistically significant at a 1% significance level. Similar findings were reported by (Addison *et al.*, 2022; Gadisa & Addisu, 2022; Geffersa *et al.*, 2022; Khonje *et al.*, 2015; Shita *et al.*, 2020, 2020; Sisang & Lee, 2023; Tesfaye *et al.*, 2016; Wake & Habteyesus, 2019; Wordofa *et al.*, 2021).

Table 9: Estimation of the treatment effect

Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
Income from Barley farm	Unmatched	59215.6532	44977.5371	14238.116	4213.03211	3.38***
	ATT	58908.5227	45734.0124	13174.5104	4376.26486	3.01***
	ATU	44520.709	58262.504	13741.7951	.	.
	ATE			13541.1477	.	.

*Source: Authors' survey result, and *** shows the significance level at 1%*

Sensitivity Analysis

Finally, the sensitivity analysis was done and the result confirmed that the estimated ATT (the average treatment effect on the treated) was not sensitive to unobserved bias up to 200%. Hence, the average treatment effect estimation result showing the income difference of birr 13,174.51 for the treated and the control groups presented in Table 9 was purely the effect of adopting improved barley varieties.

CONCLUSIONS

This study assessed the impact of adopting improved barley varieties on households' income in Ethiopia. A multi-stage sampling technique was followed to select 626 sample households from three regions. Descriptive, inferential, and econometric models were implemented in the data analysis process. The propensity score matching method was followed to match 222 adopters with 404 non-adopters. The kernel matching with a bandwidth of 0.1 was the selected matching algorithm, and it matched 220 adopters with 402 non-adopters by rejecting 2 observations from adopters, and 2 observations from non-adopters. Finally, the estimation of the treatment effect was conducted and the result confirmed that farm households who adopted improved barley varieties are getting an extra income of birr 13,174.51 compared to non-adopter households.

The results of this research confirm that adopting improved crop varieties directly contributes to improving household income and food security, and it also contributes much to reducing the agricultural yield gap and the food price through surplus production. Therefore, agricultural policies and strategies in favor of the generation, dissemination, and adoption of improved agricultural varieties are recommended to take the lives of millions out of poverty and food insecurity.

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