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Impact of Adopting Improved Wheat Varieties on Household Income in Ethiopia

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ABSTRACT

Adoption of improved agricultural technologies is a key strategy to improve production, productivity, food security, and poverty reduction. This study assessed the impact of adopting improved wheat on smallholders' income in Ethiopia. A multi-stage sampling method was followed to choose 540 sample households from Ethiopia's three main wheat-producing regions, namely the Oromia, the Amhara, and the Southern Nations, Nationalities, and Peoples (SNNP) regions. The Propensity Score Matching (PSM) was employed to match 250 adopters and 290 non-adopters and assess the impact of improved wheat adoption on farm households' income. The finding of the study confirmed that the adoption of improved wheat has a significant impact on household income. From the result, adopters earned more income of birr 26003.97 on average compared to non-adopters. This finding notifies the importance of adopting improved agricultural technologies in improving household income and livelihood. Therefore, harmonized agricultural technology generation, dissemination, and adoption are suggested to improve the income and livelihood of farm households.

INTRODUCTION

Wheat is the most important staple food crop for 2.5 billion people across the globe (Bentley *et al.*, 2022). It is the most widely grown crop in the world, with a cultivated land area of 219.2 million hectares and an annual production of 808.4 million tons in 2022. China, India, and Russia are the world's largest wheat producers with an annual production of 137.7, 107.7, and 104.2 million tons respectively. Ethiopia is the second largest wheat producer in Africa next to Egypt (FAOSTAT, 2024). Wheat is the most commercialized crop globally, with the traded amount reaching 25 % of the total production (Erenstein *et al.*, 2022).

In Ethiopia, wheat is the second most important cereal crop in terms of total production (58,078,22 tons) next to maize (107,513,69 tons), and it is the third in terms of acreage (1,867,047 ha) next to tef (2,932,670 ha) and maize (2,563,201 ha) during the main production season of 2021/2022. More than 93 % of the total production and 87 % of the total acreage comes from the two giant regions, the Oromia and the Amhara regions. Oromia accounts for 60 % of the total production and 51 % of the total wheat acreage, while the Amhara region accounts for 33 % of the total production and 37 % of the acreage in wheat. More than 4.5 million smallholder farmers are cultivating the crop. Even though the productivity of the crop has improved over the last two decades, the average productivity of the crop is yet 3.13 tons/hectare (ESS, 2022).

Despite the acreage under the crop, the productivity of wheat remained stagnant and remained behind population growth (Hodson *et al.*, 2020). For the last 20 years, the Ethiopian government has been implementing different agricultural policies and strategies intended to increase the production and productivity of smallholders. Development and dissemination of high-yielding and disease-resistant wheat varieties was the main focus, and more than 100 high-yielding, and disease-resistant wheat varieties were developed and disseminated by the national research and extension systems (Mengistu *et al.*, 2017).

The recently implemented wheat production initiatives that mainly focused on the expansion of wheat acreage, yield gap closure through the initiatives of wheat cluster farming, and the irrigated wheat initiatives had substantial in improving wheat production, and wheat self-sufficiency efforts of the country. But the national average productivity of the crop is far below the potential of the improved wheat varieties such as Abay, Boru, Daka, Danda'a, Dursa, Hidase, Wane, and others (Senbeta & Worku, 2023; Tadesse *et al.*, 2022). The national average productivity of wheat is also lower compared to the national average of the crop in some African countries. For example, the average productivity of the crop in Zambia, Egypt, Namibia, and South Africa are 7.4, 6.57, 6.0, and 4.14 t/ha, respectively (FAOSTAT, 2024).

Adoptions of improved agricultural technologies were reported to significantly reduce the yield gap, improve production and productivity, and reduce poverty and food prices by enabling marketable surplus production and achieving food security. Similar findings were reported from different African 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).

Since comprehensive empirical studies exploring the impacts of adopting wheat technologies on the improvement of household income at the national level are limited/lacking, this study was intended to assess

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the impacts of adopting improved wheat varieties on household income in Ethiopia using the primary data collected from major wheat producing areas of the country.

MATERIALS AND METHODS

Data and the Study Area

This study used primary data collected from 540 wheat producers randomly selected across major wheat-producing regions of Ethiopia. Three giant wheat-producing regions, the Oromia region, the Amhara region, and the Southern Nations and Nationalities regional states, were included in this study based on their wheat production potential. These three regions account for more than 93 % of the country's total wheat production. A multi-stage random sampling method was followed to select sample households. The regions were purposively selected based on their high potential in wheat production. Then 3 zones from the Oromia region, 1 zone from the Amhara region, and 1 zone from the southern region were randomly selected from the potential wheat-producing zones of the country. 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 2 kebeles from each district, a total of 36 kebeles were randomly selected. Finally, 15 sample households from each kebele, a total of 540 sample households, 250 (46%) adopters, and 290 (54%) non-adopters were randomly selected and interviewed for the data collection. The secondary data used in this research were collected from published and unpublished sources.

Method of Data Analysis

The collected data were analyzed using descriptive statistics, inferential statistics, and econometric models. Mean, minimum, maximum, and standard deviation were used to summarize the included socio-economic, institutional, and demographic variables. Chi-square and t-tests were applied to examine the presence of statistically significant differences between adopters and non-adopters. To perform impact assessment, a propensity score matching model (PSM) was utilized to assess the average treatment effect (ATT).

Analytical Framework

Based on the nature of the data, the Propensity Score Matching (PSM) was preferred. It is a 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. 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).

The implementation of propensity score matching (PSM) has five implementation steps. These are an 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 and Kopeinig, 2005).

Different statistical methods can be used to estimate the propensity scores. Logistic regression is the most frequently used method and was chosen for this specific research. The propensity score estimation can be expressed as:

$$P(D = 1 | X) = P(X) \qquad 1$$

From the result of Equation 1, the treatment effect for the individual observation can be estimated as:

$$\tau_i = Y_i(1) - Y_i(0) \qquad 2$$

But, the fundamental problem here is only one of the potential outcomes is observable for observation i, and we call the unobserved outcome the counterfactual outcome. Therefore, estimation of the individual treatment effect is not possible, and we focus on the average treatment effect of the population (Caliendo and Kopeinig, 2005).

If equation 1 gives us the propensity scores for both the treatment and the control group, and if the assumption of the unconfoundedness holds and there will be sufficient overlapping regions for the treatment and the control group, the average treatment effect on the treated (ATT) can be estimated as:

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

The matching quality is assessed through different techniques like the covariate balancing tests, the standard bias, the t-test, the joint significance, and the pseudo R2 (Rosenbaum & Rubin, 1985). The pseudo-square indicates how well the regressors explain the probability of participation. Therefore, there should be no systematic differences in the distribution of covariates after matching and the value of the pseudo-square should be fairly low. Similarly, the standard bias reduction ranging from 3% to 5% is perceived as good. Concerning the t-test, differences are expected before matching, but significant differences between the covariates should not be found after matching (Caliendo & Kopeinig, 2005; Rosenbaum and Rubin, 1985; Sianesi, 2004).

RESULTS AND DISCUSSION

Descriptive Results

Table 1 describes the summary of dummy variables included in the model. The result indicated that extension services and crop-specific vocational training were found to be very important and showed a positive significant relation to farm household's decision to adopt wheat technologies.

Table 1: Descriptive and inferential results of dummy variables

Variables		Adoption of wheat			χ2
		No	Yes	Total	
Sex of the household head	Female	25	17	42	0.431
	Male	265	233	498	
Access to credit services	No	269	230	499	0.740
	Yes	21	20	41	
Access to off-farm income	No	182	142	324	0.159
	Yes	108	108	216	
Access to extension contact	No	24	10	34	0.041**
	Yes	266	240	506	
Crop disease occurrences	No	42	43	85	0.387
	Yes	248	207	455	
Access to training on wheat	No	31	14	45	0.033**
	Yes	259	236	495	

Source: Authors' survey result survey result

The result in Table 2 portrays that wheat farmers in Ethiopia produce wheat products worth more than 66,081 birrs per year on average with a standard deviation of 74534.5. Similarly, the average value of wheat production for improved wheat adopters was 80820 birr, while it was 53375 birr for those non-adopters with standard deviations of 87092 and 58957 respectively. The standard deviation is very high both for treatment and control, and this indicates the diversity of wheat producers in Ethiopia as the annual wheat production ranged from 150kg to 12000 kg. Similarly, the standard deviation for wheat plot size also showed a big variation of 0.9 which is larger than the average value of the wheat plot which is 0.8. This is the result of the diversity across the wheat farmers in terms of acreage allotted to wheat farming which ranges from 0.1 hectare to 8 hectares. Moreover, the result of wheat yield also showed similar results to the area of wheat plots and the wheat yield for the same reasons.

Table 2: Descriptive and inferential results of continuous variables

Variable	Adopters (250)		Non-adopters (290)		Combined (540)		t-test
	Mean	St.dev	Mean	St.dev	Mean	St.dev	
Wheat income	80820	87092.4	53375.4	58957.0	66081.3	74534.5	4.3***
Wheat yield	1738.6	1925.0	1738.6	1925.0	1476.8	1729.2	3.3***
Livestock owned	8.0	4.1	7.7	4.3	7.9	4.2	0.8
Age of the head	48.0	13.3	48.3	12.9	48.2	13.1	-0.2
Cultivated land	1.6	1.3	1.7	1.3	1.6	1.3	-1.0
Market distance	56.7	36.1	57.7	35.0	57.3	35.5	-0.3
Wheat plot size	1.0	1.0	0.7	0.8	0.8	0.9	4.3***
Family size	6.1	2.2	6.0	2.4	6.1	2.3	0.7
Price of seed	50.9	13.1	48.4	14.9	49.6	14.1	2.1**
Land owned	1.4	1.3	1.5	1.2	1.5	1.3	-0.8
Education	1.6	0.7	1.5	0.8	1.5	0.8	0.3

*Source: Authors' survey result. *, ** & *** show the significance levels at 10, 5 & 1%*

Econometric Results

Estimation of the Propensity Score

The propensity score was estimated by regressing fifteen independent variables on the dependent variable (income from wheat farming) using logistic regression and the result is presented in Table 3. Before running the regression, the association between the included variable and the multicollinearity was checked 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	0.181	0.346	0.601	
Age of the head	-0.004	0.007	0.543	
Education of the head	0.025	0.124	0.837	
Family size	0.031	0.041	0.448	
Livestock owned	0.011	0.022	0.615	
Wheat plot size	0.488	0.123	0.000	***
Market distance	-0.001	0.003	0.612	
Off-farm income	0.139	0.191	0.467	
Extension access	0.686	0.406	0.091	*
Credit access	0.168	0.346	0.627	
Land owned	0.015	0.109	0.892	
Training on wheat	0.617	0.355	0.082	*
Cultivated land	-0.090	0.104	0.384	
Seed price	0.014	0.007	0.033	**
Crop disease	-0.132	0.252	0.599	
_cons	-2.491	0.842	0.003	***
Logistic regression		Number of obs		540
		LR chi2(15)		36.14
		Prob > chi2		0.0017
Log-likelihood	-354.74472	Pseudo R2		0.0485

*Source: Authors' survey result. *, **, and *** show the significance level at 10, 5, and 1 %*

The estimated propensity score ranged from 0.0894234 to 0.9787392 for the population with an average score of 0.462963. But, it ranged from 0.2123024 to 0.9787392 with a mean score of 0.4980613 for the adopters. Similarly, the propensity score for the non-adopters ranged from 0.0894234 to 0.9276087 with an average score of 0.4327058. Figure 1 shows the propensity score for adopters, non-adopters, and the entire sample.

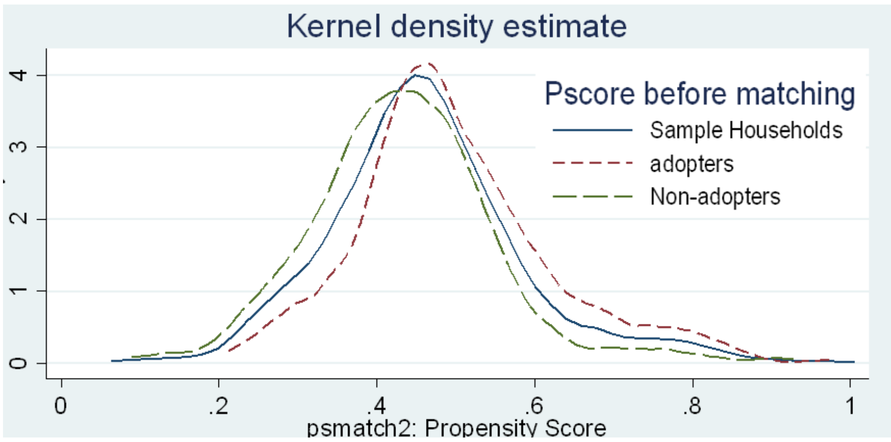

Figure 1: Summary of the propensity scores

Choosing the Matching Algorithm

To choose the matching algorithm with good matching quality, the nearest neighbor matching, the caliper matching, the radius caliper matching, and the kernel matching methods were tested. A matching algorithm is said to be good if: it matches the larger number of observations, its pseudo r-square is lower, and its mean bias is below 5%. Based on these requirements, kernel matching with a bandwidth of 0.1 was chosen for matching 533 observations out of 540, its pseudo-r-square of 0.006, and the mean bias was 3.5 %.

Restricting the Common Support Region

The common support region will be the value that is 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 control group. Therefore, the common support region will be the values of the propensity scores found between 0.2123024 and 0.9276087. Figure 2 demonstrates the common support region and the off-support regions. Based on this, 7 observations, 1 from treatment and 6 from the control group failed in the off-support region.

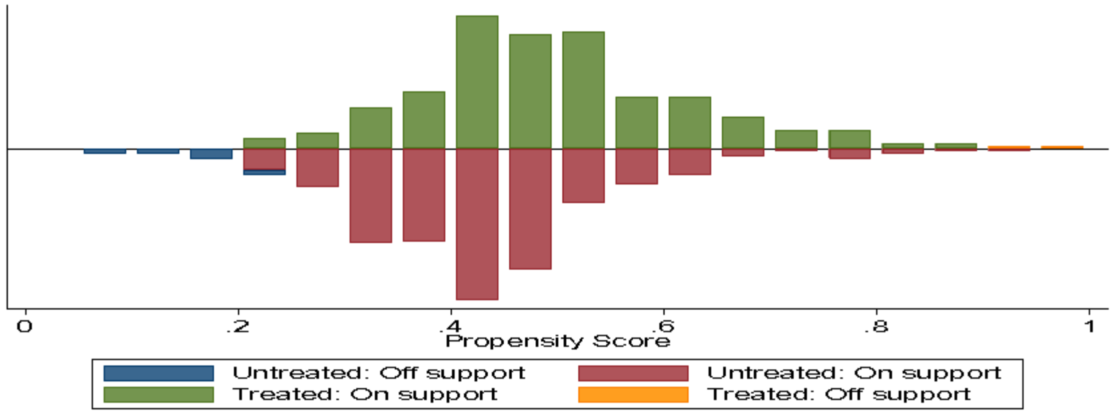

Figure 2: Summary of the on and off support regions for both treatment and control groups

Assessing the Matching Qualities

Under this sub-topic, the covariate balancing test and the estimation of the treatment effect was done. From the result in Table 4, all the included variables become non-significant after matching.

The joint significance test result presented in Table 5 also confirmed the matching quality of our model. The value of the pseudo-r-square is 0.004 after matching while it was 0.048 before matching. The mean standard bias became 3.7 percent after matching while it was 10.5 before matching. The likelihood ratio also became non-significant after matching. Therefore, it will be reasonable if we go for the estimation of the average treatment effect on the treated (ATT).

Table 4: Covariate balancing test before and after matching

Variable	Unmatched	Mean		%bias	%reduct |bias|	t-test		V(T)/ V(C)
	Matched	Treated	Control			t	P > |t|	
Sex of the head	U	0.93	0.91	6.80		0.79	0.43	.
	M	0.93	0.94	-4.00	41.80	-0.49	0.63	.
Age of the head	U	48.03	48.28	-1.90		-0.22	0.83	1.07
	M	48.01	47.55	3.50	-87.30	0.39	0.70	1.10
Education	U	1.55	1.53	2.80		0.32	0.75	0.69*
	M	1.55	1.55	1.00	64.10	0.11	0.91	0.73*
Family size	U	6.14	6.00	6.00		0.69	0.49	0.84
	M	6.12	6.20	-3.30	44.40	-0.37	0.71	0.83
Livestock owned	U	8.04	7.73	7.20		0.84	0.40	0.94
	M	7.99	7.90	2.20	70.10	0.24	0.81	0.85
Wheat plot size	U	1.02	0.70	36.50		4.27	0.00	1.65*
	M	0.99	0.90	10.20	72.00	1.10	0.27	0.86
Market distance	U	56.75	57.73	-2.80		-0.32	0.75	1.07
	M	56.94	55.93	2.80	-1.80	0.32	0.75	1.11
Off-farm income	U	0.43	0.37	12.20		1.41	0.16	.
	M	0.43	0.42	2.00	83.70	0.22	0.83	.
Extension access	U	0.96	0.92	17.90		2.04	0.04	.
	M	0.96	0.96	-2.10	88.40	-0.29	0.77	.
Credit access	U	0.08	0.07	2.90		0.33	0.74	.
	M	0.08	0.07	4.30	-50.70	0.48	0.63	.

Land owned	U	1.44	1.52	-6.70		-0.78	0.44	1.23
	M	1.44	1.46	-1.50	77.50	-0.17	0.86	1.41*
Training on wheat	U	0.94	0.89	18.70		2.14	0.03	.
	M	0.94	0.95	-3.00	84.10	-0.40	0.69	.
Cultivated land	U	1.55	1.67	-9.00		-1.04	0.30	1.06
	M	1.56	1.61	-3.70	59.30	-0.41	0.68	1.11
Wheat seed price	U	50.95	48.38	18.30		2.11	0.04	0.77*
	M	50.95	51.52	-4.00	78.00	-0.45	0.65	0.78*
Crop disease	U	0.83	0.86	-7.40		-0.86	0.39	.
	M	0.83	0.85	-7.50	-1.20	-0.84	0.40	.

*Source: Authors' compiled based on the survey result, * if variance ratio outside [0.78; 1.28] for U and [0.78; 1.28] for M*

Table 5: 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	0.048	35.66	0.002	10.5	7.2	51.5*	1.13	33
Matched	0.004	2.73	1	3.7	3.3	14.8	1.24	33

*Source: Authors' compiled based on the survey result, * if B>25%, R outside [0.5; 2]*

The result in Table 6 confirms that the adoption of wheat technology has a positive and significant impact on the farm household's income. Wheat technology adopter earns more annual income of birr 26,003.97 compared to non-adopter farm households. This result is scientifically significant at a 1% significance level. This result is similar to the finding reported by (Gadisa and Addisu, 2022; Shita *et al*., 2020; Tesfaye *et al*., 2016; Wake and Habteyesus, 2019; Wordofa *et al*., 2021).

Table 6: Estimation of the treatment effect

Variable	**Sample**	**Treated**	**Controls**	**Difference**	**S.E.**	**T-stat**
Income from wheat farm	Unmatched	83216.86	53030.59	30186.27	6441.57	4.69***
	ATT	81543.03	55539.06	26003.97	6536.57	3.98***
	ATU	53858.52	71939.10	18080.58		
	ATE			21782.13		

*Source: Authors' compiled based on the survey result, *** shows significance at 1%*

Sensitivity Analysis

Lastly, the sensitivity analysis was conducted and the result confirmed that the estimated average treatment effect on the treated was not sensitive to unobserved bias up to 200%. Therefore, the ATT result in Table 6 that is the additional income of 26003.97 birrs was the pure effect of adopting wheat technologies.

CONCLUSIONS

This study was conducted to assess the impact of adopting improved wheat on household income in Ethiopia. A multi-stage sampling technique was followed to select 540 sample households from three regions. Propensity score matching was employed for econometric data analysis. Based on the estimated propensity score, 249 adopters were matched with 284 non-adopters by using kernel matching with a bandwidth of 0.1 by rejecting 7 observations, 1 from adopters and 6 from non-adopters. The result depicted that farm households using wheat-improved seed are getting extra income of birr 26003.97 compared to non-adopter households. The finding of this research confirms that the adoption of improved agricultural technologies will directly improve household income and food security, and will also contribute much in reducing the agricultural yield gap and the food price through surplus production. Therefore, agricultural policies and strategies promoting the adoption of improved agricultural technologies should get priority to take the lives of millions out of food insecurity and poverty.

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