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Original Research

Adoption of Improved Wheat Variety and Its Impact on Agro-pastoral Household Income: The Case of Haroreys District, Somali Region, Ethiopia

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Abstract

Cereal crops, particularly wheat, are critical for enhancing household food security, generating local income, and increasing national export revenue. This study investigated the impact of adopting kingbird and kubsa improved wheat varieties on the income of rural farmers in the Haroreys area, located in the Somali regional state of Ethiopia. Using a cross-sectional design, data from 372 households were collected via multistage sampling, and propensity score matching was used to assess the impact of adopting improved wheat varieties on household income. The results suggest that the utilization of enhanced wheat cultivars has a substantial and favourable impact on household earnings, since adopters generate 19% more income compared to non-adopters. Adopters generated an average yearly revenue of 21,613.75 ETB through the sale of wheat, whereas non-adopters earned 17,611.875 ETB on average. The findings indicate that adopting improved wheat varieties significantly boosted household income, underscoring the need for policies and initiatives to support increased adoption. Interventions should consider factors like education, farm size, and resource access to enhance effectiveness and economic benefits for farming families.

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INTRODUCTION

Agriculture is a critical instrument for Ethiopia in attaining its poverty reduction and food security goals. Adopting innovative agricultural technologies, such as enhanced wheat varieties, is crucial for promoting agricultural progress, reducing poverty, and strengthening food security, particularly given that wheat is the country's major staple food product and a key source of food security. Ethiopian wheat is the 31st-largest global producer and the third-largest producer in Sub-Saharan Africa, following South Africa and Egypt, with 4.2 million quintals cultivated on 1.7 million hectares (Goshu, 2019). It ranks fourth in area and production among cereals in Ethiopia, behind teff, maize, and sorghum, contributing 15.81% of total cereal production (CSA, 2017). Despite substantial wheat output, the country relies significantly on imported wheat grains. Rural farmers in the Haroreys district encounter substantial obstacles in enhancing household revenue and ensuring food security. Although there have been advancements in wheat varieties, the rate at which they are being adopted is still modest, and the specific effect on household income has not been well studied. Currently, there is an increasing endeavor to enhance crop yield by intensifying agriculture, which involves utilizing enhanced crop variety seeds (Byerlee *et al*., 2007).

These initiatives have been led by the International Maize and Wheat Improvement Center (CIMMYT) and the Ethiopian Institute of Agricultural Research (EIAR). As a result, Ethiopia's wheat yield jumped from 2.28 quintals per hectare in 2012 to 29.67 quintals per hectare in 2018. However, production remains low compared to other places. In 2019, the government imported 1.5 million tonnes of wheat valued at around US$600 million (CSA, 2019).

This inadequate production can be linked to numerous factors, particularly limited farming technical capacity, the development of drought-prone wheat cultivars, and poorly functioning agricultural markets (Jack, 2013). According to Worku (2019), the main barriers affecting smallholders include a lack of technical dissemination and conventional management techniques. Many researches on the adoption and spread of agricultural innovations, undertaken by diverse academics and institutions both inside and outside Ethiopia, demonstrates that adopting enhanced farming techniques favourably influences earnings, food security, and alleviating poverty.

However, most of these researchers, such as Kaliba (2018), Abadi (2014), Egge (2005), Kassie *et al*. (2010), Bayissa (2010), Negash (2007), and Asfaw *et al*. (2012), primarily focused on other crops and techniques such as sorghum, maize, groundnut, sesame, and pigeon pea. Consequently, data on the adoption of improved bread and wheat varieties is crucial for addressing the low acceptance rates at the grassroots level. Previous studies, such as Tsegaye *et al*. (2012) and Shiferaw *et al*. (2014), evaluated the adoption of improved bread wheat varieties but focused on food security rather than income effects. This study aims to fill that gap by examining the impact of improved bread wheat on household income in the Haroreys district. Despite government efforts to promote these varieties, their adoption and impact on income have not been fully explored. To address this, the study uses Logit and propensity score matching (PSM) models to analyze adoption status, influencing factors, and implications for household income.

RESEARCH METHODOLOGY

Description of the Study Area

The Somali regional state is one of the ten administrations of Ethiopia, and the region consists of 11 administration zones and 93 districts. Haroreys is one of the 93 districts under the Fafan zone, which consists of 11 districts. The district was nominated in 2016 after the previous Jigjiga woreda was separated into two (North Jigjiga and South Jigjiga) in Figure 1. The study district consists of 16 kebeles and 119 sub-kebeles (BOFED, 2017).

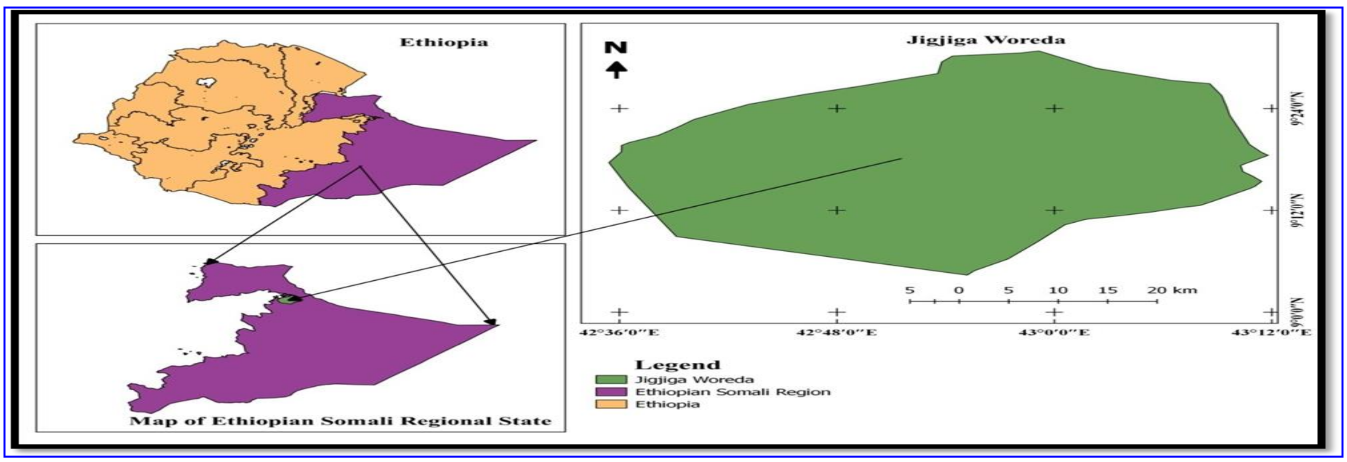

Figure 1: Map of the study area

Source: (BOFED), 2017

Population

The Woreda population is estimated at 101,430; of these, the agro-pastoralists are estimated at 58,829 (58%), and the rest are sedentary farmers (42,601). According to census data obtained from the Woreda administration, nearly all of the population resides in rural areas (Woreda administrative office, 2016). The Haroreys district is populated primarily by Muslim Somali tribes (CSA, 2007).

Agricultural production

Agriculture is the primary economic driver in the district, serving as the major source of income for its population. The region encompasses two distinct agricultural systems: agro-pastoral and pastoral production. The predominant crops cultivated in this region are sorghum, maize, and wheat. Farmers employ conventional agricultural techniques with little or no access to contemporary farming technologies. The utilization of commercial fertilizer is infrequent in the region, and farmers have limited access to fertilizer delivery (Jalleta, 2004).

Climate conditions

The research area has semi-arid climatic conditions with an average annual rainfall of 500-750 mm. The research design was cross-sectional, and data were collected during the cultivation season. The district has four different rainy seasons: GU', DEYR, HAGAA, and JILAL. The rainy season (Gu') harvesting season for land preparation and sowing goes from late March to early June. Both animals and tractors are utilized for land cultivation, and both men and women share roles in this operation. The rainy season in Hagaa lasts from late June to early September. The dry season, known as Jilal in Arabic, begins in December and lasts until early March. During jilal, the availability of water and other pastures for animals becomes scarcer, and farmers typically relocate from one location to another (BOFED, 2017).

Research Design

A cross-sectional survey approach was used in this study. Using a cross-sectional survey approach, the study's objective was to determine the factors that currently influence farmers' adoption of better bread wheat types in the Haroreys area rather than their effects over time.

Methods and Sources for data collection

Data were collected using various techniques, including a standardized questionnaire administered to 372 households, semi-structured surveys, key informant interviews, and focus group discussions (FGDs). Multistage sampling ensured the representation of both adopters and non-adopters. Secondary data was obtained from the regional agriculture research center, Haroreys Woreda agriculture office, and institutions like the Ministry of Agriculture and the central statistical agency. The data collection was conducted by eight skilled enumerators after clearly informing participants about the study's purpose.

Sample Size and Sampling Process

The sample respondents were chosen using a multi-stage sampling procedure. Haroreys woreda in the Somali regional state, famed for its wheat output, was purposively picked. Seventeen kebeles were selected at random from the woreda, totally 5460 inhabitants: Yosle 1 (1350), Harta Ali Bayle (1570), Lama-dega (1530), and Yosle 2 (1010). Kebeles with insufficient wheat production were disregarded. This selection was made possible by cooperation with key informants, kebele leaders, and development agents. Three hundred seventy-two farm family heads engaged in bread wheat production were identified using systematic random sampling throughout four rural kebeles, equal to the number of wheat producers. Since there are 10,000 total residences in the chosen kebeles, the calculation is always calculated for a limited population.

$$n = \frac{N}{1 + N(e)^2} = ------------------(1)$$

$$\frac{5460}{1 + 5460 * (0.05)^2} = 372$$

n= is the sample size for the study,

N= is the population of interest

e= is the precision level

The sample size was calculated using Israel's (1992) method: ns = (Nh/Ns) * n, where ns is the sample size for each stratum, Nh is the population in each stratum, Ns is the total population across strata, and n is the overall sample size. Table 1 shows the total households in each kebele and their respective sample sizes.

Table 1: Total number of households by kebele and their respective sample size

Kebeles	Sample Frame	Sampled Household head
Yosle 1	1350	92
Harta Ali Bayle	1570	107
Yosle 2	1010	69
Lamadaga	1530	104
Total	**5,460**	**372**

Source: Woreda administration office (2020)

Methods of Data Analysis

Data was encoded before entry and analyzed using STATA version 8.0. Descriptive statistics (mean, SD, frequencies, percentages) were used to assess household adoption status. A chi-square test evaluated qualitative traits between adopters and non-adopters, while a t-test assessed significant differences in continuous variables.

Econometric Model

Several models have been developed to analyze the adoption behaviour of farmers. In various adoption studies, binary logit and probit models have been routinely utilized (Gujarati, 2004; Maddala, 1992). The probit and binary logit models have extremely comparable cumulative probability distributions. Nevertheless, binary logit beats probit in terms of speed in calculating future likelihood. A binary logit model was employed to analyses in depth the elements driving wheat technology uptake. This model was once again chosen for its ability to depict the relative influence of technology adoption likelihood. According to Gujarati (1995), the binary logistic distribution parameters for the decision of utilization are as follows:

$$n= \frac{1}{1+e^{-z(i)}} \quad .... \quad (1)$$

Where: *p* (i): is a probability of a household being non-adopter of improved bread wheat varieties for i[th] household.

e: represents the base of natural logarithms (2.718) and

Z (i): is a function of explanatory variables (Xi) and is expressed as:

$$Z(i) = \beta_0 + \beta_1 \chi_1 + \beta_2 \chi_2 + \cdots + \beta_m \chi_m \quad (2)$$

Where β_o denotes the intercept and β_i is the slopes parameter in the maximum likelihood model. The slope describes how the log-odds in favor of not adopting technology vary as the independent variables change by one unit.

The chances are defined as the ratio of the likelihood of a household not adopting improved bread wheat varieties pi to the likelihood of a family adopting technology (1-Pi).

$$(1-pi) = \frac{1}{1+e^{z(i)}} \quad .... \quad (3)$$

Therefore;

$$\frac{(pi)}{1-pi} = \frac{1+e^{z(i)}}{1+e^{-z(1)}} = e^{z(i)} \quad .... \quad .(4)$$

$$\frac{p_{(i)}}{1-p_{(i)}} = \frac{1+e^{Z(i)}}{1+e^{-Z(i)}} = e^{\beta_o + \sum_{i=1}^{m} \beta_i y_i} \quad .... \quad (5)$$

Taking the natural logarithms of the odds ratio from equation (5) yields the binary logit model, as shown below.

$$\left(\frac{P_{(i)}}{1-P_{(i)}}\right) = In\left[e^{\beta_\circ + \sum_{i=1}^{m} \beta_i \chi_i}\right] = Z_{(i)} \quad .... \quad (6)$$

If the disturbance term U_i is considered, the binary logit model becomes:

$$Z_{(i)} = \beta_\circ + \sum \beta_i \chi_i + \cup_i \quad .... \quad (7)$$

So, the above econometric model was used in this study to identify variables that affect the adoption of improved bread wheat varieties.

Multi-collinearity Test

Before using the logit model, a multicollinearity test is necessary to check for high correlations among variables, which can obscure their individual effects (Gujarati, 2004). Variance inflation factors (VIF) and contingency coefficients are used to detect multicollinearity, with VIF specifically applied to continuous data. The following is an ordinary measure of multicollinearity related to VIF (X_i): VIF $(X_i) = \frac{1}{1-Ri^2}$

The coefficient of multiple determination (R^2) indicates multicollinearity, with higher values suggesting greater multicollinearity. For discrete variables, the contingency coefficient assesses multicollinearity by measuring the association between row and column variables in a cross-tabulation. Values range from 0 (no association) to 1 (strong association). Variables with a contingency coefficient above 0.75 are considered collinear and excluded from further analysis (Healy, 1984). The contingency coefficient was computed as follows:

$$c = \sqrt{\frac{x^2}{n + x^2}}$$

Where, c=coefficient of contingency, x^2 = a chi-square random variable and n=total sample size.

Impact assessment methods

Impact assessment studies use various methods, including propensity score matching (PSM), instrumental variable (IV) models, difference-in-differences (DD), and randomized assessments. This study employed PSM to analyze the impact of adopting improved bread and wheat types on household income, aiming to reduce selection bias and measure treatment effectiveness by comparing outcomes between adopters and non-adopters.

RESULTS AND DISCUSSION

Socioeconomic Backgrounds of Selected Wheat Adopters and Non-Adopters

The study included 372 smallholder farmers. Of these, 47% adopted various wheat varieties with defined production packages in 2021, while the remaining 53% were non-adopters (Table 2).

Table 2: Proportion of respondents by status of adoption

Adoption category	Frequency	Percent
Adopters	176	47
Non-adopters	196	53
Total	**372**	**100**

Source: Computed from own survey data (2021)

Descriptive statistics for continuous variables

The mean age of sampled respondents among bread wheat variety adopters in the research region was 41.9 years, with statistical significance indicated by t-test results. Adopters also had larger farms on average (6.5 hectares) compared to non-adopters (0.16 hectares), a difference verified by significant t-test results for farm size. Family sizes were somewhat greater among adopters (7.1) than non-adopters (7.0), with statistically insignificant variations in-home labor force involvement. Adopters lived closer to markets on average (6.9 km) compared to non-adopters (7.4 km). Livestock holdings, measured in Tropical Livestock Units (TLU), were lower among adopters (6.2 TLU) compared to non-adopters (7.3 TLU), with t-test results showing a significant difference (Table 3).

Table 3: Descriptive statistics for continuous variables

Characteristics	Adopters		Non-adopters		t-test value	P value
	Mean	SD	Mean	SD		
Age	41.9	10.4	45.6	10.0	0.0005***	0.0003
Farm size	6.5	0.17	0.16	2.3	0.80**	0.059
Livestock ownership	6.2	2.1	7.3	2.5	0.0000***	0.0000
Family size	7.1	2.4	7.0	2.4	0.81NS	0.59
Market distance	6.9	2.0	7.4	1.9	0.009***	0.004

Source: Computed from own survey data (2021). ***, **, * 1, 5 and 10% significance levels. NS

Descriptive Statistics for Categorical Variables

Table 4 presents various household parameters, including gender, educational level, off-farm participation, extension services, credit availability, farmer assessment of wheat yield, and farmer perception of input cost. The data indicates that males predominantly head households that have adopted improved bread wheat varieties, with a statistically significant gender difference. The chi-square test shows a significant association between education level and adoption, with 25.8% of non-adopters being uneducated. Off-farm participation also differs significantly, with 32.3% of adopters and 28% of non-adopters engaged in such activities. Access to extension services is significantly higher among adopters (33.6%) compared to non-adopters (17.2%). Additionally, 60% of adopters are involved in local cooperatives, whereas 40% of non-adopters are not. Credit participation is significantly higher among adopters (70%) compared to non-adopters (30%). Training participation also shows a significant difference, highlighting the link between perception and variety adoption.

Table 4. Analysis of descriptive statistics regarding categorical variables

Characteristics	Category	Adopter		Non-adopter		Ch2 test	P value
		N	%	N	%		
Sex	Female	53	14.3	89	23.9	9.8***	0.002
	Male	123	33.1	107	28.8		
Education	Illiterate	64	17.2	94	25.8	16.7	0.000
	Read and write	62	16.7	79	21.2		
	Primary & above	50	13.4	23	6.9		
Participation in off-farm activities	Yes	120	32.3	104	28	8.9***	0.003
	No	56	15.1	92	24.7		
Cooperative membership	Yes	87	23.4	62	17	12.2***	0.000
	No	89	24	134	36		
Input access	Yes	112	30.1	71	19.1	27.8	0.000
	No	125	33.6	64	17.4		
Access to credit	Yes	86	23.1	75	20.2	4.24**	0.04
	No	90	24.2	121	32.5		
Perception of input cost	Cheap	92	24.8	53	14.3	31.6***	0.000
	Moderate	56	15.1	69	18.6		
	Expensive	28	7.5	74	19.9		

Source: Computed from own survey data (2021). ***, **, * 1, 5 and 10% significance levels. NS not significant

Factors Influencing the Adoption of Improved Bread Wheat Varieties

At the 1%, 5%, and 10% significance levels, the results of the logistic regression analysis showed that six of the thirteen explanatory factors were substantially influencing the adoption of better bread wheat types (Table 5). Age, significant at the 1% level with a coefficient of -0.0414, suggested that older household heads are less likely to adopt better wheat varieties, decreasing adoption likelihood by 0.010 per year. schooling level, significant at the 5% level with a coefficient of 0.3369, showing that each additional year of schooling increased adoption likelihood by 0.08. Farm size, significant at the 1% level with a coefficient of 0.1428, suggested that a one-unit increase in farm size raises adoption likelihood by 0.035. cattle ownership, significant at the 1% level with a coefficient of -0.1536, demonstrated that more cattle reduced adoption chance by 0.038. Input access, significant at the 5% level with a coefficient of 0.8489, indicated that access to inputs increases adoption likelihood by 0.207. Market distance, significant at the 1% level with a value of -0.1316, showing that each additional kilometer from the market decreased adoption likelihood by 0.032. Lastly, input cost, significant at the 1% level with a coefficient of -0.6128, revealed that high input costs reduce adoption chance by 0.15. These data show that younger, better-educated household heads with larger farms and access to inputs are more likely to adopt improved bread wheat types, while households with more livestock, greater market distance, and higher perceived input costs are less likely to adopt.

Table 5. Result of logit output

LR chi2 (12) = 106
Prob > chi2 = 0.000
Log likelihood -204.01525

Adoption	Coefficient	std. errs	Z	p>z
SHH	.2762831	.2591213	1.07	0.286
AGE	-.0414419	.0123942	-3.34	0.001***
EDULEVEL	.3369718	.1677069	2.01	0.045**
COOPER	.3775326	.2541479	1.49	0.137
OFF-FARM	.3850477	.2599009	1.48	0.138
FARMSIZ	.1427685	.0538573	2.65	0.008***
TLU	-.1536127	.0530874	-2.89	0.004***
FAMILYSIZE	-.0388095	.0864137	-0.45	0.653
CREDIT	.0751495	.2549277	0.29	0.768
INPUT	.8489352	.2510804	3.38	0.001***
MRKETDIS	-.1315768	.061536	-2.14	0.033**
INPUTCOST	-.6127785	.1585966	-3.86	0.000***
Cons	2.286445	1.067584	2.14	0.032

Source: own survey, 2021

Impact of Adoption on Household Income

Estimation Using Propensity Score Matching

The study created a propensity score using binary logistic regression to match adopters with non-adopters of improved bread wheat (Table 6). The propensity score matching showed a low pseudo-R² value of 0.2071, indicating minimal variance in sample characteristics (Table 8).

The analysis revealed that adoption was significantly influenced by factors such as the sex and age of the household head, education, cooperative membership, off-farm activity, livestock ownership, family size, farm size, credit access, input costs, and market distance. The logit intercept was (-204.01525), negative and negligible.

Table 6. Estimation of prosperity score with a logit regression model**.**

Number of obs **= 372**				
Pseudo R^2 **= 0.2071**				
LR chi^2 (12) **= 106**				
Prob > chi^2 **= 0.000**				
Log likelihood **-204.01525**				
Adoption	**Coefficient**	**std. errs**	**Z**	**p>z**
SHH	.2762831	.2591213	1.07	0.286
AGE	-.0414419	.0123942	-3.34	0.001***
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FAMILYSIZE	-.0388095	.0864137	-0.45	0.653
CREDIT	.0751495	.2549277	0.29	0.768
INPUT ACCESS	.8489352	.2510804	3.38	0.001***
MRKETDIS	-.1315768	.061536	-2.14	0.033**
INPUTCOST	-.6127785	.1585966	-3.86	0.000***
Cons	2.286445	1.067584	2.14	0.032

Source: Own survey (2021)

Defining common support region

A common support zone between 0.0768463 and 0.935178 was determined by estimating the propensity scores, and homes outside of this range were not included in the analysis. For all homes, the mean propensity score was 0.4728 (STD 0.2539) with a range from 0.0303 to 0.9515. Adopters had a mean score of 0.6096 (STD 0.2185) ranging from 0.0827 to 0.9515, whereas non-adopters had a mean score of 0.3500 (STD 0.2185) ranging from 0.0303 to 0.8820 in Table 7.

Table 7: Distribution of estimated propensity score of farm households

Group	Observation	Mean	STD	Min	Max
All households	372	.4728458	.2538703	.0302725	.951507
Adopter	176	.6096294	.2184964	.0827441	.951507
Non-adopter	196	.3500196	.2184626	.0302725	.8820407

Source: Own survey (2021)

Matching algorism

In the common support zone, matching treatment and control households were matched, and several matching estimators were evaluated. Several criteria influenced the final choice of matching estimator, including the equal mean test (balance test), pseudo-R-2, and size of the matched sample. The pseudo-R 2 displays how effectively the regression or explanation regresses or explains the participation probability. Following matching, there should be no substantial disparities in the range of variables among the two groups, which leads to a low pseudo-R-2 (Caliendo and Kopeinig, 2005). Among the five matching estimators, the best impact estimator is one that balances all explanatory elements, has a relatively small pseudo-R2 value, and is substantial. Therefore, the kernel (0.1) matching estimator was chosen as the best estimate for matching analysis since it produced the lowest pseudo-R-2, the best balancing test, all covariates were significant after matching, and it has a larger sample size than other estimators (Table 8).

Table 8. Matching Algorism

Matching Algorisms	Income		
	Balancing test	Pseudo-R2	matched sample size
Nearest Neighbor (NN)			
Neighbor (1)	12	0.012	320
Neighbor (2)	12	0.018	340
Neighbor (3)	12	0.014	340
Neighbor (4)	12	0.013	340
Neighbor (5)	12	0.011	340
Caliper Matching (CM)			
Caliper 0.01	11	0.028	309
Caliper 0.1	11	0.027	340
Caliper 0.25	12	0.027	340
Caliper 0.5	12	0.027	340
Kernel Matching (KM)			
With band width of (0.01)	12	0.020	309
With band width of (0.1)	12	0.010	340
With band width of (0.25)	12	0.014	340
With band width of (0.5)	11	0.061	340
Radius Matching (RM)			
With band width of (0.01)	8	0.157	340
With band width of (0.1)	8	0.157	340
With band width of (0.25)	8	0.157	340
With band width of (0.5)	8	0.157	340

Source: Own survey (2021)

Verifying Common Support Condition

As illustrated by Figure 2, the total treated observation is 42 (11.2%) households are off assistance, whilst 312 (83.9%) households are in the support zone. Each treatment group is matched exclusively with control groups whose propensity scores fall inside the propensity score matching's specified common support zone. Homes residing outside of this area are eliminated from the investigation; hence, 13 treated and 5 untreated homes were dropped from the inquiry.

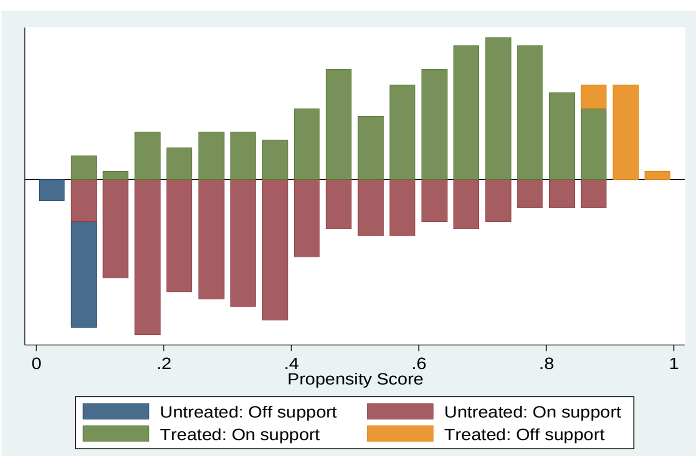

Figure 2: Propensity score

Testing the balance of propensity score and covariates

The next stage is to utilize several ways to verify if the propensity score and variables are balanced after picking the optimum matching algorithm. Rosenbaum and Rubin (1983) suggest that achieving balance in propensity score matching (PSM) is crucial to eliminate confounding variables, requiring tests like the t-test and chi-square test. Table 9 displays mean standardized bias before and after matching, suggesting widespread bias reduction. Before matching, standardized disparities varied from −42.3% to 123.1% but fell within acceptable ranges post-matching. Rosenbaum and Rubin (1983) stress the need for balance for trustworthy PSM outcomes. Covariate balancing tests in Table 9 reveals that standard bias differences varied from 21% to 56% before matching, reducing to 1.2% to 11.2% after matching, below Rosenbaum's (1983) 20% criterion. The main goal of evaluating propensity scores is to ensure consistent distributions of essential features across groups (Caliendo & Kopeinig, 2008). The chosen kernel (0.1) technique successfully achieved covariate balance across adopter and non-adopter households, essential for robust effect analysis (Table 9).

Table 9. Propensity score and covariate balance test

Variables	Unmatched	Mean		%reduction		t-test	
	Matched	Treated	Control	%bias	bias	T	p>t
Pscore	U	.61092	.34938	119.3		11.49	0.000
	M	.5773	.57258	2.2	98.2	0.20	0.839
Sex	U	.69886	.54592	31.9		3.06	0.002
	M	.68987	.66924	4.3	86.5	0.39	0.695
Age	U	41.909	45.622	-36.3		-3.50	0.001
	M	42.443	42.169	2.7	92.6	0.24	0.811
Education Level	U	.92045	.63776	37.9		3.66	0.000
	M	.86076	.90924	-6.5	82.9	-0.56	0.578
COPMSHP	U	.49432	.31633	36.8		3.55	0.000
	M	.48734	.48176	1.2	96.9	0.10	0.921
OFFARM	U	.68182	.53061	31.2		3.00	0.003
	M	.65823	.60379	11.2	64.0	1.00	0.318
FARMSIZ	U	6.5398	5.6378	39.1		3.77	0.000
	M	6.2911	6.4303	-6.0	84.6	-0.55	0.583
TLU	U	6.1705	7.2908	-48.7		-4.67	0.000
	M	6.3418	6.176	7.2	85.2	0.68	0.499
FAMILY	U	6.0341	5.658	24.9		2.41	0.017
	M	5.9177	5.9024	-1.0	95.9	0.09	0.927
ACREDIT	U	.48864	.38265	21.4		2.07	0.040
	M	.47468	.44505	6.0	72.0	0.53	0.599
INPUT ACCESS	U	.63636	.36224	56.9		5.47	0.000
	M	.59494	.60034	-1.1	98.0	-0.10	0.922
MARKETDIS	U	6.8523	7.3929	-27.4		-2.64	0.009
	M	6.943	6.972	-1.5	94.5	-0.13	0.895
INPUTCST	U	.63636	1.1071	-61.0	78.9	-5.86	0.000
	M	.6962	.79562	-12.9		-1.15	0.251

Computed: Own survey (2021)

The low pseudo-R^2 value and negligible likelihood ratio test suggest that the matching process equalized the distribution of covariates between adopter and non-adopter households. This indicates that the matching technique effectively balanced the groups, allowing for a valid comparison of the impact of improved bread and wheat types between similar households.

Matching quality test

Table 10 displays that the standardized mean difference for overall covariates used in the propensity score for income (4.9% before matching) is reduced to about 0.010% after matching, indicating that the matching was successful. Moreover, the p-values of the likelihood ratio tests demonstrate that the combined significance of the covariates was discarded after matching but never.

Table 10: matching quality test

Sample	Ps R2	LR chi2	p>chi2	Mean Bias	Med Bias	B	R	%Var
Unmatched	0.208	106.95	0.000	44.1	36.8	118.9**	0.98	38
Matched	0.010	4.500.	0.985	4.9	4.3	23.9	0.82	0

Source: own survey (2021); * If B>25%, R outside [0.5; 2]

Average treatment effect

This part includes evidence of the impact of improved bread and wheat variety adoption on household income. The average treatment impact (ATT) assessed by PSM for income with a kernel 0.1 matching result demonstrates that enhanced bread wheat variety adoption affects family income statistically (Table 11). According to the PSM model results, households that participate in the adoption of improved bread wheat varieties have enhanced their average income to 21613.75 Birr compared to 17611.875 Birr for non-adopters. This suggests that improved cultivars affect household income. This implies that improved wheat types boost household income by 19%. This finding is discordant with earlier studies on the impact of other crops on food security. According to Shiferaw et al. (2014), the adoption of enhanced cultivars greatly enhances food security.

Table 11: Average treatment on the treated (ATT)

Variable sample	Treated	Control	Difference	S. E	T-stat
ETB					
Unmatched	21461.3636	17692.3469	3769.0167	520.880527	7.24
ATT	21613.75	17611.875	4001.875	828.682715	4.83

Source: computed from own survey, 2021

Sensitivity analysis

After determining the ATT of the gathered data, the next diagnostic that must be conducted is a sensitivity analysis. The logic behind this is to check the sensitivity of the estimated treatment impact to unmeasured factors that affect both treatment assignment and the outcome variable (Dehejia, 2002). If the study is not influenced by unobserved characteristics, the effect of unobserved variables is zero. As a result, the chance of involvement is solely governed by observed attributes.

However, if there is unobserved bias, even two people who have similar observed features have a different chance of obtaining the treatment. A sensitivity analysis was performed based on this premise. Table 12 indicates that the effect of adopting improved bread wheat types on household income remained unchanged even when adopter and non-adopter households were allowed to differ in their probability of being treated up to gamma = 0.5 (100%) in terms of unobserved factors.

Table 12: Result of sensitivity analysis using Rosenbaum bounding approach.

Outcome variable	e^{Y} =1	e^{Y} =1.25	e^{Y} =1.5	e^{Y} =1.75	e^{Y} =2
HH net Income	0.000	0.000	0.000	0.000	0.000

Source: Own survey result, 2021.

CONCLUSION

Modern agricultural technologies play a key role in boosting food security and household income. The study evaluated the adoption of improved bread wheat types and the factors influencing this adoption in Haroreys Woreda, Ethiopia. The result suggests that education, farm size, and availability of agricultural inputs strongly improve the adoption of improved wheat varieties, while characteristics such as age, and the cost of inputs provide hurdles. Particularly, adopters of these improved types reported a 19.5% gain in income compared to non-adopters, underlining the economic benefits. Therefore, it is necessary for government programs to prioritize the distribution and acceptance of improved wheat growers. Extension services should focus on educating farmers about the advantages and optimal farming practices associated with these wheat varieties. Promoting the adoption of improved wheat varieties is essential for enhancing farmers' income and strengthening food security.

Data Availability

All data generated are included within the article. Furthermore, datasets are available from the corresponding author upon request.

COMPETING INTERESTS

The authors declare no competing interest.

AUTHORS' CONTRIBUTIONS

MAM conceived the study, contributed to the study design, and performed the analysis. GRM and BF contributed data duration and visualization. SMS reviewed and edited the manuscript. All authors read and approved the final manuscript.

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REFERENCES

Abadi teferi alemaw, (2014). Impact of improved maize varieties adoption on smallholder farmers’ marketed maize surplus in Oromia regional state. A dissertation submitted in partial fulfilment of the requirements for the degree of Master of Science in agricultural and applied economics of Sokoine University of agriculture. morogoro, Tanzania.

Asfaw, S., Kassie, M., Simtowe, F., & Lipper, L. (2012). Poverty reduction effects of agricultural technology adoption: micro-evidence from rural Tanzania. Journal of Development Studies, 48(9), 1288-1305.

Asfaw, S., Shiferaw, B., Simtowe, F., & Haile, M. (2011). Agricultural technology adoption, seed access constraints and commercialization in Ethiopia. Journal of Development and Agricultural Economics, 3(9), 436-477.

Bayissa, G. (2010). Adoption of improved sesame varieties in Meisso district, West Hararghe Zone, Ethiopia (Doctoral dissertation, Haramaya University).

BOFED (Bureau of Finance and Economic Development) (2017). Five years Somali regional states' local economic implication report

Byerlee, D. R., Spielman, D. J., Alemu, D., & Gautam, M. (2007). Policies to promote cereal intensification in Ethiopia: A review of evidence and experience.

Caliendo, M., & Kopeinig, S. (2005). Some Practical Guidance for the Implementation of Propensity Score Matching. Discussion Paper No. 1588, DIW Berlin Department of Public Economics. Konigin-Luise-Str. 5, 14195. Forschungsinstitut zur Zukunft der Arbeit Institute for the Study of Labor. https://doi.org/10.2139/ssrn.721907

Caliendo, M., & Kopeinig, S. (2008). Some practical guidance for the implementation of propensity score matching. Journal of economic surveys, 22(1), 31-72.

Challa, M., & Tilahun, U. (2014). Determinants and impacts of modern agricultural technology adoption in west Wollega: the case of Gulliso district. Journal of Biology, Agriculture and Healthcare, 4(20), 63-77.

CSA (2017). Agricultural Sample Survey: Report on Area and Production of Major Crops. Addis Ababa, Ethiopia.

CSA (2019). Agricultural sample survey. Report on area and production of major crops.

CSA: Agricultural Sample Survey, 2007/08 (2000 E.C.), Volume II: Report on Livestock and livestock characteristics (Private peasant holdings). Statistical Bulletin 417. Central Statistical Agency (CSA), Federal Democratic Republic of Ethiopia, Addis Ababa; 2008.

Dehejia, R. H., & Wahba, S. (2002). Propensity score-matching methods for non-experimental causal studies. Review of Economics and statistics, 84(1), 151-161.

Egge, M. (2005). Farmers’ evaluation, adoption and sustainable use of improved sorghum varieties in Jijiga Woreda, Ethiopia. An M. Sc Thesis Submitted to School of Graduate studies, Alamaya University.

Goshu, D., Getahun, T. D., & Oluwole, F. (2019). Innovation opportunities for wheat and faba bean value chains in Ethiopia (Vol. 4, No. 5). FARA Research Report.

Gujarati DN (1995). Basic Econometrics, 3rd Edition, McGraw-Hill, Inc, New York. 838p.

Gujarati, D. N. (2004). Basic Econometrics (fourth edi). *New Yok: McGraw-Hill Inc*.

Healy, F.J. (1984). Statistic: A Tool for Social Research. Wadsworth Publishing Company, California.

Israel, G. D. (1992). Determining sample size.

Jack, B. K. (2013). Market inefficiencies and the adoption of agricultural technologies in developing countries.

Jalan, J., & Ravallion, M. (2003). Does piped water reduce diarrhea for children in rural India?. Journal of econometrics, 112(1), 153-173.

Jalleta, T. (2004). Participatory evaluation of the performance of some improved bread wheat (Triticum aestivum) varieties in the Jijiga plains of eastern Ethiopia. Experimental agriculture, 40(1), 89-97.

Kaliba, A. R., Mazvimavi, K., Gregory, T. L., Mgonja, F. M., & Mgonja, M. (2018). Factors affecting adoption of improved sorghum varieties in Tanzania under information and capital constraints. Agricultural and Food Economics, 6, 1-21.

Kassie, M., Shiferaw, B., & Muricho, G. (2010). Adoption and impact of improved groundnut varieties on rural poverty: evidence from rural Uganda.

Maddala, G. S., & Lahiri, K. (1992). Introduction to econometrics (Vol. 2, p. 525). New York: Macmillan.

Negash, R. (2007). Determinants of adoption of improved haricot bean production package in Alaba special woreda, southern Ethiopia (Doctoral dissertation, Haramaya University).

Rosenbaum, P. R., & Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. Biometrika, 70(1), 41-55.

Shiferaw, B., Kassie, M., Jaleta, M., & Yirga, C. (2014). Adoption of improved wheat varieties and impacts on household food security in Ethiopia. Food policy, 44, 272-284.

Tsegaye, D., Dessalegn, T., Dessalegn, Y., & Share, G. (2012). Analysis of genetic diversity in some durum wheat (Triticum durum Desf) genotypes grown in Ethiopia. African Journal of Biotechnology, 11(40), 9606-9611.

Worku, A. A. (2019). Factors affecting diffusion and adoption of agricultural innovations among farmers in Ethiopia case study of Ormia regional state Westsern Sewa. International Journal of Agricultural Extension, 7(2), 137-147.

Zegeye, T. (2001). Adoption of improved bread wheat varieties and inorganic fertilizer by small-scale farmers in Yelmana Densa, and Farta districts of Northwestern Ethiopia. CIMMYT.