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Impact of Wheat Cluster Farming Practice on Smallholder's Asset Building in Arsi Zone of Ethiopia

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Abstract: Agriculture is the main focus of Ethiopia's economic development. It accounts for about 32.7% of the country's GDP (NBE, 2020). Wheat is one of the major cereal crops produced by smallholder farmers in Ethiopia. Wheat demand is rising quickly in Ethiopia despite efforts to improve wheat production. Recently, to curb this problem, the government of Ethiopia has set up a cluster farming system for high-potential crops like wheat as a means of improving productivity and maximizing the income of smallholder farmers. In light of the problems and the research gaps identified, this study seeks to address the impact of wheat cluster farming practices on stallholder's asset building in the Arsi Zone of Ethiopia. Data was collected from 383 sample wheat-producing households. The data was analyzed using descriptive statistics and propensity score matching model. The propensity score matching model of the average treatment effect on the treated result revealed that wheat cluster farming participation had a significant impact on the smallholders' asset building. It has been found that, on average, participation in wheat cluster farming has increased smallholders' asset building by ETB 8014.13 (148.69$) for wheat cluster participants as compared to non-participants. Hence it was concluded that cluster farming has improve wheat production which is the major source of income to build asset of the study areas smallholders. Therefore, stakeholders should develop strategies to promote and scale up cluster farming practices. As a result, smallholder farmers will use the extra wheat produced by cluster farming to accumulate more assets and thus raise their standard of living.

Keywords: Cluster Farming, Asset Building, Productivity, Propensity Score Matching

1. Introduction

Agriculture contributes significantly to the Ethiopian economy. It is the main focus of the Ethiopian government's plan for the growth and development of the country's economy. It accounts for about 32.7% of the country's gross domestic product [1]. It also provided employment opportunities for about 65.6% of the total population in 2020 [2].

Cereal crop production is the dominant sub-sector in Ethiopian agriculture [3]. It creates about 60% of the rural job opportunities for the Ethiopian economy. It is also a source of more than 60% of the total calorie intake of the country's population [4]. *Teff*, wheat, maize, and sorghum are the most important cereal crops cultivated in Ethiopia [1].

According to CSA [5] wheat is the fourth most important cereal crop cultivated after *teff*, maize, and sorghum and the third in production after maize and *teff* in Ethiopia. About 4.7 million farm households are directly dependent on wheat production [6]. Ethiopia is one of the major wheat-producing countries in Africa, which accounted for about 20% of the Africa's total wheat production in 2019 [7]. More than 90% of Ethiopia's wheat production is grown mainly by smallholder farmers [8, 9]. Ethiopia produces about 4.8 million metric tons of wheat, which was cultivated on 1.8 million hectares of land in 2020/21 [1]. The central highland areas of Ethiopia, such as Arsi, West Arsi, Bale, and East Shewa zones, cover about 42% of Ethiopia's wheat production, with 1.89 million tons in 2018 [10].

Rapid urbanization and population growth greatly increase the demand for wheat products like wheat flour, bread, biscuits, pasta, macaroni, and spaghetti [11]. Even though Ethiopia is a potential wheat producer, a huge gap between production and consumption due to increasing demand for wheat products makes Ethiopia an importer of wheat. The Agricultural Transformation Agency indicates that Ethiopia has more than 600 small and large flour mills with a total production capacity of 4.5 million tons of wheat flour per year [12]. Domestic demand for wheat is estimated at 6.3 million tons.

Wheat is an important staple food crop and also the main source of income for smallholder farmers in the Arsi Zone [5, 7]. The production of wheat is dominated by smallholder farmers [6]. Despite being the most extensively grown crop in the area, wheat's productivity is relatively low by global standards [5, 7, 11, 13, 14]. This could be caused by a lack of implementation of modern farming practices [13, 15-19]; a lack of use of agricultural input technology packages [20-23]; low technical efficiency [24] or environmental factors [25-27]. Low wheat productivity in potential wheat-producing areas forced the country to import wheat for several years in order to meet the growing demand for wheat [1, 15].

Recently, to curb this problem, the government of Ethiopia adopted a cluster farming system for high-potential agricultural commodities as a means of improving crops productivity, poverty reduction and smallholders' income maximization. To address this, Ethiopia's GTP II aims to implement cluster farming practices to increase production and productivity of high-potential crops [12]. Cluster farming's aims to effectively integrate and coordinate interventions for prioritized high-potential commodities (like wheat in the Arsi Zone) and geography in order to transform subsistence production into market-oriented production that can meet local demand and produce for export markets [28].

Cluster farming is a farming practice that is implemented as part of a complete farming package. It creates real profit by merging several smallholder farms into a solid entrepreneurial group of clusters that is capable of sharing both the benefits and the challenges [12]. Cluster farming is a farming practice that is growing crops on adjacent farmland with the aim of increasing productivity. Increasing productivity means producing more output with the same amount of inputs or using fewer inputs to produce the same level of output. The cluster farming practice improve productivity by using improved seeds at the same time, using fertilizers that are suitable for the same agro-ecology, benefiting from the same technical advisory support, and harvesting their crops with the same machinery [29].

Various empirical studies undertaken in the Arsi Zone have examined the impact of agricultural technology practices on the income of smallholders [13, 16, 22, 30-31]**.** Such studies do capture the impact of technology participation on the income of smallholders, though most of the studies do not show how much of the income generated by the implementation of new farming practices was converted to the asset wellbeing of the smallholder producers.

Although there are literatures focusing on evaluating the impact of improved wheat technologies adoption on wheat productivity and the income of smallholder wheat producers in the Arsi zone, the issue is not well studied in relation to the impact on smallholder farmer asset building. Since wheat cluster farming is a recently implemented farming practice in the Arsi zone, to the knowledge of the researcher, no effort has been made similar to the current study, which tries to explore the impact of wheat cluster farming on the asset building status of smallholder wheat producers. Therefore, the motivation for this study arises from the need to fill this knowledge gap.

Evaluating the impact of wheat cluster farming on smallholders' asset welfare is crucial. This helps to assess whether the income gained from producing wheat under cluster farming could be used to improve the living standards of smallholders through asset accumulation. Therefore, researching the impact of participating in wheat cluster farming on smallholders' farmer asset building is very essential to generating up-to-date empirical evidence. It is also important to identify factors determining participation in wheat cluster farming. Accordingly, this study has been intended to assess the impact of cluster farming on smallholder farmer asset building and to identify determinants of participation in wheat cluster farming in the Arsi zone of Ethiopia.

2. Materials and Methods

2.1. Description of the Study Area

Arsi Zone is found in the south-eastern highlands of the Oromia National Regional State of Ethiopia. It is located between 6° 45'N and 8° 58'N and 38° 32'E to 40° 50'E. According to the 2021 population projection, the total population of the Arsi zone is 3.71 million [6] (Figure 1).

According to USDA [10], the Arsi zone is one of the major wheat producing areas in the south-eastern Ethiopian highlands, mainly known for its widespread wheat production and called the "wheat belt of Ethiopia." Wheat production comprises about 7.2 million quintals (41%) of the total annual cereal production of the Arsi zone through the engagement of 360,697 wheat producers. Arsi zone wheat production in 2020/21 constitutes about 22% and 12.5% of the Oromia region and Ethiopia's wheat production, respectively, which makes it the leading wheat-producing zone in Ethiopia. Wheat production accounts for about 39% of the total cereal cultivated area in the Arsi zone [6].

The Arsi zone was chosen by the Minister of Agriculture to undertake wheat cluster farming in Ethiopia due to its potential for wheat production. Wheat cluster farming has been practiced in Ethiopia in general and in the Arsi zone in particular since 2014. It is expected to play an important role in increasing wheat productivity in the country [12]. Farms that are located near each other as a geographic cluster benefit from being able to utilize the same logistics, such as transportation, improved input supplies, machines, extension services, and a shared pool of skilled labor [32].

Figure 1. *Study area map. Source: Authors 2021.*

2.2. Sources and Methods of Data Collection

Multistage sampling (both purposive and random) methods were employed to select the districts, *kebeles* (the lowest administrative unit), and the target sample households of the study. In the first phase, three potential wheat-producing districts, namely, Hetosa, Lode Hetosa, and Tiyo, were selected through a purposive sampling technique in consultation with the Arsi Zone Agriculture Office and the Arsi Zone Cluster Farming Coordination Office. The districts are the areas where wheat cluster farming was widely implemented.

In the second stage, eight *kebeles* (four *kebeles* from the 18 kebeles in Hetosa district, two *kebeles* from the 12 *kebeles* in Lode Hetosa district, and two *kebeles* from the 13 *kebeles* in Tiyo district) were randomly selected using a simple random sampling technique from the three districts. The allocation of *kebeles* to districts was done based on their number of wheat producers.

In the third stage, using the fresh list of wheat producer households (both participants and non-participants in wheat cluster farming) living in each *kebele,* which was available at the district offices, as a sampling frame, sample households were selected using a systematic random sampling technique from each kebele. The total sample size is determined using a formula given by Kothari [33] that affords the maximum sample size to ensure the anticipated precision. The formula given by Kothari is as follows:

$$n = \frac{Z^2 pqN}{e^2(N-1)+Z^2pq} = \frac{(1.96)^2(0.5)(0.5)(401{,}404)}{(0.05)^2(401{,}404)+(1.96)^2(0.5)(0.5)}$$

$$= 385{,}508.4/1004.4 = 383.4 \quad (1)$$

Where: n is the anticipated sample size; Z is the standard cumulative distribution that corresponds to the level of confidence with the value of 1.96; e is the desired level of precision; p is the estimated proportion of an attribute present in the population with the value of 0.5 as recommended by Israel (1992) to get the desired minimum sample size of households at 95% confidence level and ±5% precision; q=1-p; and N is the size of the total population from which the sample is drawn. Thus, 383 sample households, out of which 134 are from cluster farming (treatment) and 249 from non-cluster farming (control), were selected from nine *kebeles* using random sampling with probability proportional to size.

2.3. Data

Both primary and secondary data were used for the study. The primary data was collected through personal interviews using a structured questionnaire. Primary data was collected in order to address each of the objectives of the study. The data was collected from a sample of respondents selected randomly.

The types of data covered include wheat production, wheat cluster farming practices, types of farming inputs employed, prices of inputs and outputs, sources of income, information on land and livestock holdings, asset possession, and other institutional, socio-economic, and demographic characteristics of households from both groups of wheat producers.

The questionnaire was pre-tested on twenty sample households, five from each group (users and non-users of wheat cluster farming), before conducting the actual field survey to check its relevance. It was revised according to the feedback from pre-testing. Focus group discussions with selected wheat producers were carried out to better understand the issue and to produce more in-depth information on some of the survey findings. It is also used to understand the perceptions of the wheat producers that may not be adequately captured by the field survey. Enumerators who are familiar with the study areas were selected and trained in order to collect data from wheat producers. In addition to the formal questionnaire survey, focus group discussions at the village level and field observations on a few randomly selected wheat producer households were done. The final survey data were collected from June to September 2021.

Secondary data about wheat cluster farming, its distribution, prices and yields of wheat and other annual crops that are major sources of income to the smallholder wheat producers, population, type of credit, and other technology available were collected by using a checklist. The major sources of secondary data include the CSA, ATA, Minister of Agriculture, ATA Oromia Regional Office Cluster Coordination, Arsi Zone, and selected district agriculture offices.

2.4. Method of Data Analysis

The information gathered for this study was examined using econometric analytic techniques as well as descriptive statistics. A descriptive statistics analysis was used to analyze the demographic and socio-economic characteristics of the wheat producer households. The econometric analysis was done by employing the propensity score matching (PSM) method to assess the impact of wheat cluster farming on smallholders' asset building and to identify factors determining the participation decisions of smallholders in wheat cluster farming. It was chosen from among the non-experimental methods because it does not require baseline data and is considered one of the best alternatives to experimental design for minimizing selection biases. According to Leta *et al*. [34] and Workineh *et al*. [4], participation in the wheat cluster farming practice was viewed as a treatment that wheat producers' households went through, and the estimation of wheat producers' outcomes post-participation in the wheat cluster farming practice is an evaluation of the outcome variable.

Rosenbaum and Rubin [35] found an econometric theory for PSM. Consider wheat producer smallholders that participated in wheat cluster farming (a treatment group) and wheat producer smallholders that did not participate in wheat cluster farming (a non-treatment group). Let $P(X_i)$ be the probability of participating in wheat cluster farming, or the propensity score, with X_i being a vector of independent variables. Based on the probability of participation P(Xi), a match can be found for each of the wheat producer households that participated in wheat cluster farming. The purpose of estimating a propensity score is to balance households that have participated in wheat cluster farming with households that have not participated, based on observable characteristics. The impact of the wheat cluster farming practice (treatment effect) can then be computed by averaging the conditional effect over the propensity score distribution in the participating group as follows:

$$\theta^e/_{i=1} = E_{p(x)}\{\{E(Y_{i1}/P(X_i)Z_i = 1) - E(Y_{i0}/P(X_i)Z_i = 0)\}/Z_i = 1\} \quad (2)$$

Let $P(X_i)$ be the probability of participating in wheat cluster farming, or propensity score, with X_i being a vector of explanatory variables. Finding the match for a participant household based on a vector of characteristics is equivalent to finding the match based on the probability of participating in wheat cluster farming practice, conditional on the vector of farm household characteristics, i.e., $P(X_i) = \Pr(Z_i = 1/X_iP)$. As a result, the problem is reduced to matching participant and non-participant households based on their conditional probabilities of accessing the wheat cluster farming practice, a scalar variable that can be estimated using an empirical model such as a logit or probit model, which yields nearly identical results. This study employed the probit regression model to identify factors determining the participation decisions of the farmers (and derive the propensity scores). The steps to be followed are discussed as follows:

The PSM technique used in this study followed different steps. Estimating propensity scores is the first step in the PSM method. Propensity scores can be estimated by means of either a logit or probit binary model. These binary models were used to estimate the probability of a unit's exposure or assignment to the program. The probability of participating in the wheat cluster farming practice is conditional on a set of observable covariates that may affect participation in cluster farming.

The study used a probit regression model to estimate propensity scores, which consist of a range of predictor variables that are most likely to influence both participation in cluster farming and the outcome variable. The covariates used to estimate the propensity score were similar to those used for the identification of factors affecting participation in wheat cluster farming, as indicated in Table 1.

The next key step after the estimation of propensity scores for wheat cluster farming participants and non-participants was identifying the common support region between participants and non-participants. To ensure that the estimation of treatment effects is not biased, sufficient overlap propensity scores for the treated and control groups are required. The common support region (overlap condition) for the estimated propensity score was constructed based on the summary statistics of the wheat cluster farming participants and non-participants. In setting the common support conditions, minima and maxima comparisons were made. The basic criterion of this approach is to delete all observations out of the overlapping region whose propensity score is smaller than the minimum and larger than the maximum in the opposite group. Thus, the common support region was determined by taking the maximum of the minimums and the minimum of the maximums for the two groups' propensity scores. There should be a balance between the mean propensity score of treated and untreated individuals. If the balancing property is not satisfied, a corrective measure should be taken.

Selecting the best matching algorithm was the other important step in the PSM method of the study. The alternative matching estimators (algorithms) were searched for in matching the cluster participants (treatment) and non-participant (control) households in the common support region. The final matching estimator was selected based on the mean bias result, pseudo-R^2 result, and matched sample size. Sianesi [36], Dehejia and Wahba [37] used a large matched sample size, low pseudo-R2, a large number of insignificant variables after matching (covariance balance test or balancing test), and joint insignificance of all regressors of logit or probit analysis after matching to select the best estimator.

It is necessary to evaluate whether the propensity scores and the matching method can balance the distribution of covariates between cluster participants and non-participant groups. This method aids in comparing the condition before and after matching based on the propensity score and covariates. The average propensity score and mean of the variables between the treated and control groups can be compared using balancing tests [38]. The t-test for mean equality, values of pseudo-R^2, the chi-square test for joint significance of the variables, and the decrease in mean standardized bias between matched and unmatched households were used to test the power balance. Applying the chosen matching method allowed for the verification of the propensity score and covariate balance.

Calculating the average treatment effect on the treated (ATT) was the important step of the PSM model of the study. The participation in the wheat cluster farming practice was viewed as a treatment that wheat producers' households went through, and the estimation of wheat producers' outcomes post-participation in the wheat cluster farming practice is an evaluation of the treatment effect [4, 34]. The ATT measures the impact of wheat cluster farming participation on the asset building status of smallholders' farmers who actually participated in cluster farming, rather than across all wheat producers who potentially could have participated in wheat cluster farming. ATT is calculated as:

$$ATT = E[Y(1) - Y(0) \| G = 1] = E[Y(1) \| G = 1] - E[Y(0) \| G = 1] \quad (3)$$

Where Y is asset building status (potential outcome), G represents household participation in cluster farming, with a value equal to 1 if a household participates and 0 otherwise, and X represents the explanatory variables.

One of the most challenging and contentious problems with observational studies is choosing and determining which variables should be included in a statistical model [39]. Relevant but omitted variables related to the matching of wheat cluster farming participants with non-participant households cause bias in intervention outcomes. [40]. To decrease the stated problem, sensitivity analysis is a method used for the evaluation of treatment effects. The basic question to be answered here is whether the finding about treatment effects may be affected by unobserved factors (hidden bias) or not. In light of this, a sensitivity analysis was carried out for the outcome variable (asset building among smallholders).

A sensitivity analysis was performed to determine whether or not the treatment effect findings were influenced by unobserved factors (hidden bias). The estimation of treatment effects with matching estimators is based on the selection of observable characteristics. However, a hidden bias might arise if there are unobservable variables that affect assignment to treatment and the outcome variable at the same time [40]. Because the sensitivity analysis supports it, the robustness of the estimated intervention results will be included in this study, primarily to ensure whether the inference made about the impact of participating in wheat cluster farming, which has higher asset building status increment than non-participant households, is reliable or not.

Participation in wheat cluster farming practices, which is a dummy variable with values of 1 or 0, is the dependent variable for the participation decision in the probit model. The outcome variable (smallholders' farmers asset building) is a continuous variable measured in ETB and refers to the value of asset (physical and/or financial) obtained from wheat income by smallholders in 2020/21. Physical assets include: productive assets, living houses, warehouses, livestock, household goods, and consumer durables purchased with the wheat income gained in the study period. Financial assets also refer to the amount of money saved by the wheat producer from the wheat income gained during the study period. The independent variables used to determine participation decisions and estimate propensity scores with the probit model of this particular study are indicated in Table 1.

Table 1. *Description of variables hypothesized to affect participation decision.*

Variables	Measurement	S.n
Age of household head	Continuous (Years)	-
Sex of household head	Dummy (1male, 0 female)	+
Education status	Continuous (years)	+
Dependency ratio	Continuous (%)	-
Wheat experience	Continuous (Years)	+
Credit access	Dummy (1, get, 0 otherwise)	+/-
Extension visits	Continuous (Count)	+
Livestock holding	Continuous (TLU)	+
Off/ non-farm income	Continuous (ETB)	+/-
Labour access	Dummy (1, if get, no, 0)	+
Wheat farm size	Continuous (hectare)	+
Farmer-farmer extension	Dummy (1, if get, no, 0)	+
Mechanization access	Dummy (1, if get, no,0)	+
Oxen ownership	Continues (Count)	+
Distance to FTC	Continues (km)	-
Topography	Dummy (1, if gentle, no, 0)	+/-

Source: Own preparation from theoretical, empirical literatures and author's view

3. Result and Discussion

3.1. Results of Descriptive Statistics

Results of the descriptive analysis as indicated in Table 2 showed that the mean amount of wheat produced by the sampled households was 55.2 quintal. The average production per household in the area is by far greater than the national average wheat production (12.6 quintal/hectare) in the same year [6]. The proportion of the mean wheat yield of the cluster participants' households was 64.7 quintal, whereas the mean wheat yield of non-cluster participants was 50.1 quintal. The descriptive analysis of the variable showed that there was a significant difference in wheat production between participants and non-participants in wheat cluster farming.

The study area's wheat producers get income, which is the source of asset building, mainly from sales of wheat, sales of other crops, sales of livestock, and off/non-farm activities. However, sales of wheat constitute the major source of income for all groups of sampled wheat producer households in the study area. The mean gross income (the value of the total wheat yield at the current market price) of wheat for sampled households in the *meher* production season in the study area was ETB 176768.70 (3279.57$).

Table 2. *Economic characteristics of sampled households.*

Variable	Total sample	Non-participant	Participant	t ratio
Farm income	209.9 (122)	190.5 (107.5)	245.9 (140)	-4.3***
Wheat income	176.7 (106)	160.3 (91.7)	207.2 (125)	-4.2***
Yield	55.2 (33)	50.1 (28.6)	64.7 (39)	-4.1***
Farm (ha)	1.44 (0.83)	1.41 (0.84)	1.5 (0.82)	-0.97

Source: Survey results.

Note: Note: *** and ** represent significance at 1% and 5% significance levels, respectively. Income indicated in 1000

3.2. Econometric Results

3.2.1. Factors Determining Participation in Wheat Cluster Farming

This section demonstrates the estimation process, identifies factors determining participation in wheat cluster farming, and presents the results of the PSM method. The predicted probability values of participation in wheat cluster farming practice using the probit model for all cluster participants (treated group) and non-participants (control group) wheat producer households.

Before estimating the probit model, the data was checked for multicollinearity. Variance Inflation Factor (VIF) was used to check multicollinearity among independent variables. As indicated in Table A1, VIF was less than 10. The result indicates that there is no serious problem with multicollinearity. Thus, none of the explanatory variables were dropped from the estimated model.

Table 3. *Estimation result of probit model on factors determining wheat cluster participation.*

Explanatory variables	Coefficients	Robust Std.err	Z
Age of household head	-0.015**	0.01	-1.49
Sex of household head	-0.43	0.54	-0.81
Education level	0.21**	0.1	2.11
Credit access	0.004***	0.0001	3.22
Extension contacts	0.079***	0.017	4.6
Livestock holding	0.039	0.045	0.87
Off/non farm income	0.03**	0.004	0.17
Farm size	0.08	0.008	1.01
Labor	0.007	0.023	0.32
Wheat experience	-0.076**	0.034	-2.2
Dependence ratio	-0.06	0.25	-0.24
Farmer to farmer extension	0.22	0.15	1.52
Oxen	0.147	0.146	1
Mechanization	0.44***	0.11	4.02
Constant	-3.68**	1.22	-3
Pseudo R2	0.27		
LR Chi-Squared	73.7		
Prob.>Chi-squared	0.000		
Sample size	383		

Source: Survey results.

Note: *** and ** represent significance at 1% and 5% probability levels, respectively.

The dependent variable is a dummy, indicating households' participation in wheat cluster farming practice, with a score equal to 1 or 0 otherwise. The explanatory variables used are variables that explain the cluster farming participation characteristics of the wheat producer households. The probit regression result, given on Table 3, reveals that fourteen explanatory variables were hypothesized to determine wheat cluster participation. According to the computed coefficients, seven explanatory variables have a substantial effect on participation in wheat cluster farming at various probability levels.

The probit regression result indicates that the education level of the household head, access to credit services, extension contacts, off/non-farm income, and access to mechanization services do positively influence the decision to participate in wheat cluster farming. On the other hand, the age of the household head and wheat production experience have a negative role in households' decisions on wheat cluster farming participation.

3.2.2. Analysis of Wheat Cluster Farming Impact on Smallholder's Asset Building

I. Estimation of the propensity scores

The PSM technique begins by estimating propensity scores. To calculate propensity scores, the research employed a probit regression model. As indicated in Table 3, the likelihood ratio with the chi-square distribution (LR chi2(14) = -149.14) is significant at less than the 1% probability level. The outcome of the probit estimation shows that the null hypothesis, which states that all coefficients are concurrently equal to zero, is rejected. The value of count R^2, which is the measure of goodness of fit of the probit model result, shows that the correctly predicted percent of sample households is 39.8%. This indicates that there were no symmetric differences in the distribution of covariates between participants and non-participants in the wheat cluster farming practice. The result shows that participation in wheat cluster farming was fairly random.

II. Identifying common support region

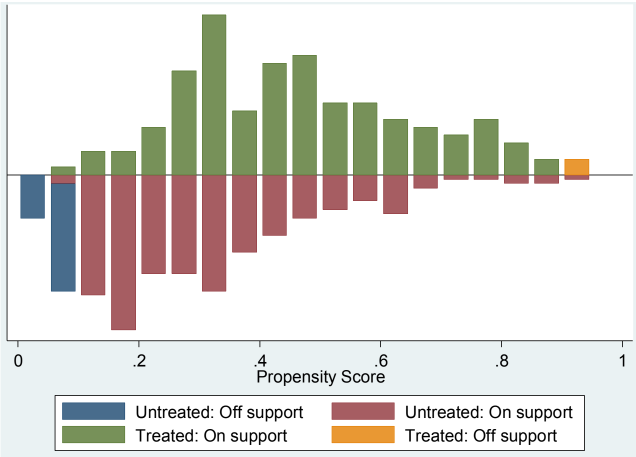
Identifying the common support region between participants and non-participants is the next key step after the estimation of propensity scores for wheat cluster farming participants and non-participants The estimated propensity score for wheat cluster participants had a minimum of 0.0979355 and a maximum of 0.9133318, with a mean propensity score of 0.4700. whereas the estimated propensity score for wheat cluster non-participants was a minimum of 0.0226726 and a maximum of 0.9029357, with a mean propensity score of 0.22852 (Table 4). Accordingly, based on comparing the minima and maxima of the propensity score of participants and non-participants, the minimum propensity score of non-participants was 0.0226726 and the maximum propensity score of participants was 0.9133318. Thus, the common support region of the data lies between 0.0226726 and 0.9133318. Consequently, households with a propensity score of less than the minimum (0.0226726) and larger than the maximum (0.9133318) are off-support and not considered for matching and estimation of the average treatment effect.

Table 4. *Summary of estimated propensity score of households.*

Propensity score	Observation	Mean	Std. Dev.	Minimum	Maximum
Cluster participants	131	0.47	0.1928	0.0979355	0.913332
Cluster non-participants	249	0.2852	0.1853	0.0226726	0.902936
Total households	383	0.3498	0.2074	0.0226726	0.913332

Source: Survey result

As a result of the overlap condition, 37 observations, of which 35 were from non-participants and 2 from cluster participants, were found to be outside of the common support region. Due to the overlap condition, about 9.6% of households were excluded from the observations used to analyze the impact of participation in wheat cluster farming on the outcome variable (treatment effect on the treated). From the result, it can be concluded that the study has enough support regions and satisfies the requirement for sufficient overlap.



Source: Survey data, plotted by psgraph

Figure 2. *Propensity scores distribution and common support region.*

Figure 2 also depicts the distribution of households with respect to the estimated propensity scores and the common support region. The upper halves of the histogram show the propensity score distribution of wheat cluster farming participant households, while the bottom halves show the propensity score distribution of non-participants. The yellow color in the bars indicates the propensity score of cluster participants (treated as wheat producers) that are outside the common support region. Similar to this, the blue color of the bars represents the propensity score of non-participants (untreated wheat producers) who are outside the common support zone.

III. Selecting a matching algorithm

A matching algorithm that best fits the criteria was carefully chosen. According to the result of the study indicated in Table A2, the matching estimator that had a large matched sample size, a small pseudo-R^2, a large number of insignificant variables (insignificant t-test of variables after matching), and a small mean standardized bias was the kernel matching (bwidth of 0.25). Therefore, all the estimation results and discussions would be the outcome of a kernel matching algorithm with a band width of 0.25, which satisfies all the listed criteria.

IV. Testing the balance of propensity score and covariates

The balance of propensity scores and covariates was checked by applying the selected matching algorithm (kernel bandwidth of 0.25). Table 5 shows the results of the covariate and propensity score balance tests before and after matching. The standardized difference in propensity score and covariates before matching was in the range of -21% and 67.6%. After matching, the remaining standardized difference in propensity scores for all covariates lies between -10.1% and 15%. The criteria have been satisfied because the individual covariate mean difference between participants and non-participants is less than 25%, as suggested by Rosenbaum and Rubin (1985). According to the requirements, a high degree of covariate and propensity score balance between the cluster participants and non-participant samples is produced by the matching procedure (Table 5).

The result of t-stat shows that seven variables were statistically significant at less than a 5% probability level before matching (Table 5). This indicates that households that were participants and non-participants in wheat cluster farming were significantly different in terms of certain features before matching. Whereas, after matching, all variables have statistically insignificant differences. It indicates that differences in covariates between wheat cluster farming participants and non-participants were removed after matching. Consequently, the matching process has created a covariate balance between the participant's and non-participant's samples. In the end, the assumption of no selection bias was satisfied, and thus it is viable to proceed with the matching procedure.

Table 5. *Balancing test of the covariates after matching.*

Variable	Sample	Mean		Standardized bias		T-ratio	
		Treated	Control	Bias%	(%) Reduc	t-value	P>ltl
Pscore	Unmatched	0.499	0.269	110.5	99.8	10.5	0.000
	Matched	0.427	0.426	0.2		0.01	0.988
Age	Unmatched	46.73	49.06	-18.6		-1.77	0.078
	Matched	46.73	48.0	-10.1	45.6	-0.82	0.411
Sex	Unmatched	1.052	1.068	-6.7		-0.62	0.538
	Matched	1.053	1.058	-6.6	2.0	-0.14	0.892
Education	Unmatched	2.35	2.57	-17.0		-1.53	0.561
	Matched	2.34	2.37	-1.8	89.3	0.28	0.783
Creditacc	Unmatched	0.22	0.202	4.2		0.27	0.015
	Matched	0.22	0.212	0.3	92.1	0.28	0.981
Extension	Unmatched	16	10.3	67.6		6.31	0.000
	Matched	15.51	14.52	15.0	77.8	0.48	0.632
Livestock	Unmatched	2.94	2.87	2.7		0.25	0.285
	Matched	2.95	2.84	4.8	-77.8	-0.67	0.801

Variable	Sample	Mean		Standardized bias		T-ratio	
		Treated	Control	Bias%	(%) Reduc	t-value	P>ltl
Off/non-farm inc	Unmatched	14765	13982	2.7		0.25	0.806
	Matched	14853	16033	-4.0	-50.7	-0.38	0.702
Farm size	Unmatched	1.501	1.41	10.4		1.17	0.90
	Matched	1.509	1.45	6.4	38.3	0.61	0.981
Labor	Unmatched	6.17	5.38	13.4		1.26	0.214
	Matched	6.21	5.90	5.3	60.5	0.73	0.466
Experience	Unmatched	23.04	25.35	-21.7		-1.56	0.119
	Matched	23.04	23.98	-8.9	59.2	-0.43	0.669
Dependence	Unmatched	1.10	1.09	1.9		0.14	0.541
	Matched	1.10	1.12	-1.5	21.3	0.23	0.887
Farm_farext	Unmatched	0.664	0.57	19.4		-0.14	0.541
	Matched	0.666	0.66	0.4	97.9	1.21	0.887
Family size	Unmatched	5.4	5.21	11.2		1.06	1.232
	Matched	5.8	5.6	2.6	72.5	0.98	1.03
Oxen	Unmatched	1.95	1.85	11.8		1.08	0.28
	Matched	1.94	1.97	-2.3	80.3	-1.09	0.276
Mechacc	Unmatched	1.45	1.54	19.7		1.84	0.066
	Matched	1.52	1.52	0.8	96.4	0.05	0.959

Source: Survey result

According to Sianesi [36], after matching, the distribution of covariates between the treatment and control groups shouldn't vary systematically. The likelihood ratio test on the joint significance of all covariates in the logistic model, which was not rejected before matching, was rejected after matching. The result of pseudo-R^2 should be low after matching as an indicator of no systematic differences in the distribution of covariates between participant and non-participant sample groups. Accordingly, the value of Pseudo-R^2 which was 0.398 before matching, declined to 0.011 after matching.

The result was a standardized mean bias before matching for covariates used to estimate the propensity score. It was 19.8%. The result is reduced to 4.2% after matching (Table 6), which is between 5 and 2% as suggested by Caliendo and Kopeinig [41] and Resenbaum and Rubin [35]. Thus, the results revealed that the selected matching estimator, in this case, kernel matching with a bandwidth of 0.25, successfully balanced the distribution of covariates between participants and non-participants in wheat cluster farming practice.

Table 6. *Overall balance indicators of covariates.*

Sample	Pseudo-R^2	LR chi2	P >chi2	Mean Bias
Unmatched	0.398	77.64	0.000	19.8
Matched	0.011	4.74	0.989	4.2

Source: Survey result

The PSM result of the kernel (bandwidth 0.25) algorithm estimate identified a total of 346 observations. Of these, 214 observations are from the wheat cluster participants (treatment) group, and the other 132 observations are from the non-participant (control) samples. The results of the tests indicate that the chosen matching algorithm is the best match method for the data in the study. Thus, it can be feasible to use the matched propensity score result of the data to estimate the impact of wheat cluster farming on the outcome variable (smallholders' asset building).

3.2.3. Impact of Wheat Cluster Farming on Smallholder's Asset Building

The difference in average asset values between cluster participants and non-participants can then be interpreted as the impact of the wheat cluster farming practice. The matching result shows that the difference in smallholders' asset building value between cluster participants and non-participant households is significant (Table 7).

The average treatment effect on the treated of the research offers proof of whether or not wheat cluster farming has significantly changed smallholders' asset building. As shown in Table 7, the estimation result offers a helpful indication of the statistically significant impact of wheat cluster farming practice on smallholders' asset building, measured in ETB. It has been found that, on average, participation in wheat cluster farming has increased smallholders' asset building by ETB 8374.29 (155.37 $) for wheat cluster participant households as compared to non-participant wheat producer households, which is significant at the 1% level of significance. The study's findings are in line with those of Regasa and Degye [42] and Leta *et al.* [34], who stated that adoption of new farming practices had a favorable effect on smallholders' asset holdings.

Table 7. *Wheat cluster farming impact on asset building.*

Variable	Sample	Treated Mean (ETB)	Control Mean (ETB)	Difference (ETB)	S. E (ETB)	T-stat
Asset	Unmatched	39397.08	29359.5	10037.5	2212.17	4.54
Building	Matched	39458.16	31083.87	8374.29	2583.4	2.76***

Source: Survey results.
Note: *** represent significance at 1% significance level.

A sensitivity analysis was performed in order to check for unobservable biases in the outcome variables. Rosenbaum

Bounding was the approach that was used to test the sensitivity analysis of the computed impact on the smallholder's asset building. As indicated in Table A3, the critical level of $e^{g}=1$ (first column) over which the causal inference of significant wheat cluster impact must be questioned. The second column of the table shows those outcome variables that bear statistical differences between treated and control households in their impact on the asset building estimate.

The results of the sensitivity analysis shows that inference for the impact of wheat cluster farming practice does not change, even though cluster participant and non-participant households were allowed to differ in their odds of being treated up to 200% ($e^{g}=3$**)** in terms of unobserved covariates**.** As a result, impact estimates (ATT) are not sensitive to unobservable (hidden) selection bias, as they are solely the result of wheat cluster farming practice.

4. Conclusion and Recommendations

The purpose of this study was to assess the impact of wheat cluster farming practice on smallholders' farmers asset building and to generate information on factors determining wheat cluster farming participation. Field surveys were conducted to gather data of the 2020/21 wheat production season to obtain study results. By employing a multistage sampling technique, a total of 383 wheat producer households (survey data was collected from 134 cluster participants and 249 non-participants) were sampled from eight *kebeles* in three districts (Hetosa, Lode Hetosa, and Tiyo) in the Arsi Zone of the Oromia region, Ethiopia. Data collected from smallholder wheat producers was analyzed using both descriptive statistics and PSM method.

The descriptive statistics of the data highlighted marked differences between wheat cluster participants and non-participants. Access to credit services, extension contacts, off/non-farm income, and access to mechanization services do positively influence the decision to participate in cluster farming. The results of the research show that smallholder wheat farmers who participate in wheat cluster farming have better asset holding status, as measured in Ethiopian Birr, which is worth ETB 8374.29 (about 155.37 dollars). It was therefore determined that cluster farming has a favorable and significant effect on wheat output, which is the primary source of income used by smallholder farmers in the study area to build their assets. Therefore, stakeholders should develop strategies to promote and scale up cluster farming practices by providing better extension, credit and agricultural mechanization services to wheat producing farmers which are very vital to implement wheat cluster farming. As a result, the extra wheat produced by cluster farming will be used by smallholder farmers to increase the value of their assets and raise their standard of living.

Authors Contributions

Getachew Nigussie is the corresponding author and did all activities of the research, from data collection to writing and editing of the manuscript. The other authors, Mengistu Ketema, Zekariyas Shumeta and Kedir Jemal, participated in the commenting and editing of all aspects of this paper, from the data collection to the final report.

Declarations

Ethics Approval and Consent to Participate

Not applicable.

Availability of Data and Materials

The datasets used for the study are available from the corresponding author upon request.

Conflict of Interests

Authors have no competing interests related to the publication of this research paper.

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Appendix

Table A1. *Multicollinearity test on factors affecting cluster participation.*

Variable	VIF	1/VIF
Wheat Experience	5.23	0.19
Age of household head	5.16	0.19
Wheat farm size	1.55	0.64
Labor	1.31	0.76
Off/non-farm income	1.22	0.82
Extension contacts	1.17	0.85
Dependence ratio	1.07	0.93
Livestock holding	1.07	0.93
Education status	1.07	0.93
Oxen holding	1.06	0.94
Mean VIF	1.73	

Source: Survey result

Table A2. *Performance of matching algorithms.*

Matching estimator	Psedo R^2 after matching	Number of insignificant variables after matching	Matched sample size	Mean Bias
Nearest neighbor matching				
Nearest neighbor 1	0.042	13	346	9.7
Nearest neighbor 2	0.032	12	346	11.8
Nearest neighbor 3	0.015	14	346	9
Nearest neighbor 4	0.015	14	346	8.8
Nearest neighbor 5	0.012	14	346	7.3
Caliper matching				
Radius 0.01	0.045	14	315	9.2
Radius 0.1	0.04	13	346	9.7
Radius 0.25	0.04	13	346	9.7
Radius 0.5	0.04	13	346	9.7
Kernel matching				
Bandwidth 0.01	0.013	14	315	5.2
Bandwidth 0.1	0.013	14	346	4.6
Bandwidth 0.25	0.011	14	346	4.2
Bandwidth 0.5	0.058	13	346	5.8

Source: Survey result

Table A3. *Result of sensitivity analysis using Rosenbaum bounding approach.*

Gamma e^g =	Asset building
1	P<0.002
1.25	P<0.000
1.5	0
1.75	1.70E-06
2	1.40E-07
2.25	1.20E-08
2.5	9.90E-10
2.75	8.20E-11
3	6.80E-12

Source: Survey result

Note: e^g (Gamma) = log odds of differential due to unobserved factors where Wilcoxon significance level for each significant outcome variable is calculated

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