Letters in Economic Research Updates ISSN: 3068-9236

PRIME OPEN ACCESS

Volume 2, Issue 2

Research Article

Date of Submission: 08 Apr, 2026
Date of Acceptance: 05 May, 2026
Date of Publication: 14 May, 2026

Assessing the Impact of Cluster Farming on Productivity and Commercialization in Ethiopia: An Analysis Using Propensity Score Matching

Yonnas Addis Mihertea*

Assistant Professor of Agribusiness and Value Chain Management, Wolkite University, Wolkite, Ethiopia

***Corresponding Author:** Yonnas Addis Mihertea, Assistant Professor of Agribusiness and Value Chain Management, Wolkite University, Wolkite, Ethiopia.

Citation: Mihertea, Y. A. (2026). Assessing the Impact of Cluster Farming on Productivity and Commercialization in Ethiopia: An Analysis Using Propensity Score Matching. *Lett Econ Res Updates, 2*(2), 01-12.

Abstract
Smallholder farmers with limited resources can sustain their agricultural farming through cluster farming, however many smallholder farmers are still indeterminate to the impact of cluster farming in Ethiopia. In this study, the impact of teff cluster farming participation on productivity and commercialization in Central Ethiopia, particularly in Sodo district of Guraghe Zone. The study employed a cross-sectional survey of 196 households (92 participants; 104 non-participants), selected through multistage sampling procedure. The data used in this study were collected in 2021/22 production year. Family size positively influence teff cluster farming participation and it was statistically significant at 10% level. Credit accesses, and off farm income positively determine teff cluster farming participation at 1% level of significance. On the other hand the age and educational level of a household negatively influence smallholder teff farmer's participation in cluster farming and this was statistically significant at 5% level. A probit model estimates propensity scores and nearest-neighbor matching (k=2 chosen from several algorithms) is used to estimate ATT effects. The study revealed positive, statistically significant impacts of cluster farming on productivity (≈ +2.25 qt/ha) and commercialization (≈ +6.58 percentage points). The study suggests the positive role of cluster farming in boosting agricultural productivity and farmer's level of commercialization. Strengthen institutional service provisional mechanisms and building skill for family labour management through diverse strategies is essential for scaling up cluster farming participation and thereby farm level productivity and commercialization.

Keywords: Cluster Farming, Commercialization, Productivity, Impact, Propensity Score Matching

Introduction
The Ethiopian agriculture is predominantly characterized by smallholder farming; it contributes to 94% of agricultural GDP and 63% of the employment opportunities [1]. Agricultural cluster initiative is one of the main policy interventions in the agricultural sector introduced during the first Growth and Transformation Plan (2010/11 – 2014/15) [2]. Farm level productivity, income, commercialization and food security are expected to be increased through agricultural cluster farming participation [3-7]. The use of shared farm resources like tractors and combine harvesters and improved agricultural inputs through cluster farming leads strong market linkage and better farm productivity [8].

The role of cluster farming in improving yields, market access, and rural livelihoods through initiatives such as the Agricultural Commercialization Clusters (ACC) program and other integrated agricultural extension systems are invaluable [2]. Cluster farming initiatives in Ethiopia focuses on specific high-value crops such as teff, wheat, maize, sesame, horticultural crops, and malt barley. It is expected to contribute to better productivity and commercialization [6]. Despite recognizing the transformative potential of cluster farming, Ethiopia's smallholder farmers encounter significant barriers to cluster farming adoption due to inadequate infrastructure, low literacy levels, entrepreneurial ability, risk preferences, social capital, plot quality, proximity to service centers and insufficient financial resources [9-12]. Poor institutional service and resource sharing experiences complicate the adoption process [13].

Previous studies on cluster farming have mainly focused on how various demographic, socioeconomic, and institutional factors influence the adoption of cluster farming and its impacts on productivity and income poverty with an emphasis on adoption and [4,14-18]. While some research has examined the effects of adopting cluster farming on productivity particularly focusing on other part of Ethiopia, the specific impacts of teff cluster farming in this context remain insufficiently explored, in the study area [19].

These studies mainly targeted identifying determinants of cluster farming participation, mainly on limited set crops like wheat and maize. This crop specific information limited the validity of research in diverse production system. Specifically, previous studies conducted in this field were conducted in different agro ecological setting and institutional environment than the target study area in this study, where environmental variations, marketing infrastructure and local governmental engagement level determine the performance of cluster farming [20]. These different contexts limit the scope of the existed literatures. So, there is notable research gap in assessing the impact of cluster farming on productivity and commercialization in Sodo district, East Guraghe zone of Ethiopia. This study is the first comprehensive study to analyze cluster farming impacts in teff farming, thereby addressing empirical and contextual scanty of the literatures.

The study employed Propensity Score Matching (PSM) to assess the impact of teff clustter farming engagement on productivity and commercialization level. The study assumed that PSM successfully reduces selection bias due to observable difference among participants and non-participants of the program. PSM is more flexible to functional form assumptions by balancing covariate directly and this makes more applicable than Multinomial Endogenous Switching Regression, which requires on strong and hard to validate instrumental variables [21,22]. On the other hand, Difference-in-Differences (DID) requires strong baseline data and parallel trend assumptions that are hard to meet in heterogeneous and sluggishly expanding cluster farming program [23,24].

Although doubly robust estimator particularly IPWRA improve efficiency, PSM is more transparent and valid that cluster farming participation is largely relied on observable farmers and farm characteristics like farmers experience, land size, extension and market accesses and these characteristics [25-27]. The study assumed a matched comparison group with similar characteristics, PSM provides a reliable counterfactual where randomized assignment to the treatment group is impossible and baseline data are limited.

In the study area, Sodo district in East Guraghe Zone, about 49,000 ha of land covered with various crops, of which the majority (80%) has been cultivated by cluster farming and 60% of the total cultivated lands were using mechanization [28]. About 62% of kebeles apply cluster farming on teff, wheat and maize. Accessible land topography, soil fertility, suitable ecology and weather condition makes the district more convenient for agriculture. Despite the anticipated advantages of cluster farming in time efficiency and task simplification, the specific impact of cluster farming on farm level productivity and commercialization have not been adequately addressed. The study aimed analyzing the impact of teff cluster farming participation in farm level teff productivity and commercialization level. This study hypothesized that cluster farming significantly increases productivity and commercialization level of teff farmers in sodo district of East Guraghe Zone, Central Ethiopia.

In this study, Kebele selection was purposive (highest potential). This threatens external validity and may temper generalization claims. The study targeted high-potential producing kebeles because they provide favorable conditions that make it easier to demonstrate the impact of cluster farming. In Ethiopia, cluster farming is more practiced in areas usually have better infrastructure, farmer organization, and improved access to extension services, which support effective implementation of cluster farming. The study assumed that focusing on such kebeles allows generating clearer and more reliable evidence of productivity and commercialization impacts of cluster farming participation. Also, productivity is measured as output per unit land and it is collected through farmers recalling. To minimize recall bias the survey was conducted at the end of the production year.

Conceptual Framework of the Study

The conceptual framework of the study is presented in figure 1 explains the interrelationships in the study, the main variables involved and how they are interrelated. The study hypothesized that participation in cluster farming, teff productivity and commercialization is affected by factors related to household characteristics, ownership of asset and institutional characteristics [3].

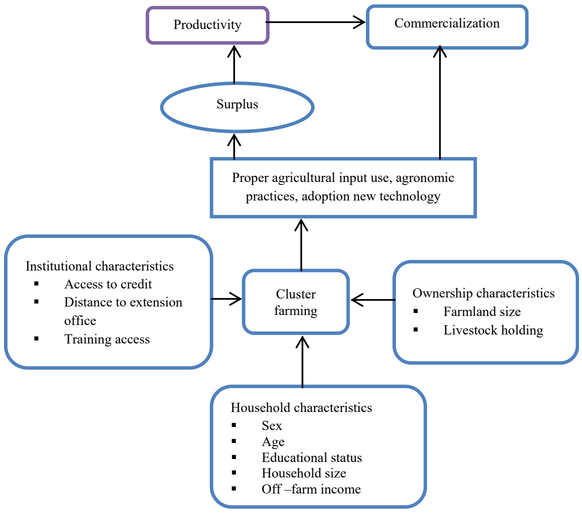

Figure 1: Conceptual Framework of the Study (Adopted from Abate S., 2021)

Materials and Methods

Data Sources and Sampling Procedure

The study collected data from both from primary and secondary sources. The cross sectional primary were collected from randomly selected farm households in 2021/22 production year and administered through structured interview schedule. Sodo District Office of Agriculture, published reports, and peer-reviewed literatures were major sources of secondary data used in this study.

A three-stage sampling procedure was employed in this study. In the first stage, four kebeles namely Negesa, Rufenso, Agamsenado, and Kela were purposively selected due to their exposure in highest potential and experiencing cluster farming. In the second stage, farm households were stratified into cluster farming participants and non-participants. The total sample of 196 farm households (92 participants and 104 non participants was obtained using systematic random sampling from the total populations of 4,670 (1451 participants and 3219 non participants). was employed to determine the required sample size and the variance of attribute in the population which is assumed to 7% considering homogeneity attribute of farm households [29]. The determined sample is adequately satisfying PSM requirements by ensuring satisfactory treatment control overlap (common support), sufficient variation in covariates, and balanced representation across strata. The distribution by kebele and participation status is shown in Table 1.

Kebeles	Total	Cluster farming participation			
		Total population (N)		Sample (n)	
		Participant	Non participant	Participant	Non participant
Rufenso	1685	395	1290	29	36
Negesa	1100	378	722	28	29
Kela	993	353	640	20	22
Agamsenado	892	325	567	15	17
Total	**4670**	**1451**	**3219**	**92**	**104**

Table 1: Sample Size Distribution by Kebeles and Cluster Farming Participation

Own computation, 2021/22

Source: Sodo Woreda Agricultural and Rural Development Office

Methods of Data Analysis

Descriptive and Inferential Statistics

The study employed means, standard deviations, and independent t-tests to compare teff productivity and commercialization among two groups. Agricultural commercialization was measured using households commercialization index (HCI), which quantifies the share of output marketed. The existed studies by used HCI to compute households commercialization level [2,30,31]. Therefore, in this study

HCI is computed as:

$$\text{HCI} = \frac{(\text{gross value of teff marketed})}{\text{gross value of produced}}$$

Teff productivity was measured as output per hectare.

$$\text{Productvity} = \frac{\text{crop output(Qt)}}{\text{area planted(ha)}}$$

Propensity Score Matching (PSM)

To evaluate the casual impact of cluster farming on productivity and commercialization, the study employed Propensity Score Matching (PSM). PSM is chosen to minimize selection bias from observable characteristics that possibly influence that influence farmers participation decisions in cluster farming. The propensity score was estimated using probit model by including demographic, socio economic, and institutional variables. After estimating propensity score, teff farm households were matched using nearest neighbor matching (NN) algorithm with two neighbors (NN (2)) and replacement was chosen which provided the best covariate balance and minimize bias. The analyses were done using STATA version 14.

Although PSM reduces selection bias from observable characteristics, it has the following limitation: 1) PSM cannot control for unobserved heterogeneity, any omitted variable correlated with both the treatment and outcome may bias estimates. 2) The results depend heavily on the quality of matching and the availability of sufficient common support between participants and non-participants households. 3) PSM assumes conditional independence that after controlling for covariates, treatment assignment is random and this is an assumption that is strong in observational agricultural data. These limitations are acknowledged when interpreting the findings of this study.

Variables and descriptions	**Total sample (N=196)**	**Cluster farming participation**		**Expected sign**		
		Participant (N=92)	Non Participant (N=104)	Cluster farming participation	Commercialization level	Productivity (yield)
	Mean (SD)	**Mean (SD)**	**Mean (SD)**			
Sex of household head (1 if male, 0 female)	0.683 (0.466)	0.67 (0.471)	0.69 (0.463)	+	+	+
Age of household head (Years)	45.78 (7.756)	44.3 (7.98)	47.08 (7.34)	-	-	
Year of schooling (number)	5.73 (3.45)	5.14 (3.32)	6.25 (3.50)	+	+	+
Family size (number)	2.95 (1.175)	3.09 (1.271)	2.82 (1.542)		-	+
Land size (Hectare)	2.38 (0.961)	2.54 (0.879)	2.24 (1.011)	+	+	+
Livestock ownership (TLU)	5.43 (1.674)	5.32 (1.615)	5.54 (1.725)	+	+	+
Farming experiences (Years)	18.23 (5.47)	17.9 (5.46)	18.47 (5.503)			+
Non-farm income participation (1 if yes, 0 otherwise)	0.51 (0.5)	0.652 (0.478)	0.39 (0.491)	+	+	+
Membership to cooperative (1 if yes, 0 otherwise)	0.55 (0.498)	0.60 (0.49)	0.51 (0.502)	+	+	+
Extension contact (Number)	10 (4.56)	10.76 (4.63)	9.47 (4.43)	+	+	+
Accesses to credit (1 if yes, 0 otherwise)	0.5 (0.5)	0.60 (0.49)	0.40 (0.493)	+	+	+
Distance to market (KM)	2.89 (1.671)	0.65 (0.478)	2.82 (1.54)	-	-	-
Level of commercialization (%)	37.19 (15.34)	40.22 (16.02)	34.52 (14.27)			
Quantity of teff produced (Qt)	11.88 (6.37)	14.91 (7.74)	9.19 (2.911)			
Productivity of teff (Qt/ha)	11.16 (4.678)	11.88(3.60)	10.51 (5.389)		+	
Cluster farming participation (1 if participant, 0 otherwise)	0.469 (0.5)				+	+

Table 2: Descriptive Statistics Results and Expected Signs of Independent Variables Own Computation, (2021/22)

Result and Discussions

Descriptive Statistics Result

As depicted in Table 2 both groups are predominantly male-headed households, with a slightly higher proportion among non-participants (69%) than participants (67%). On average, participants are younger (44.3 years) compared to non-participants (47.08 years), suggesting that younger farmers might be more inclined to adopt cluster farming. Interestingly, non-participants have a slightly higher level of education (6.25 years) than participants (5.14 years), yet this does not lead to better outcomes in productivity or commercialization.

Participants generally have larger landholdings (2.54 hectares) than non-participants (2.24 hectares), which correlates positively with higher productivity and commercialization levels. Non-participants have slightly more livestock (5.54 TLU) than participants (5.32 TLU), but this difference does not significantly impact overall outcomes.

Participants benefit from greater access to extension services (10.76 contacts per year compared to 9.47 for non-participants) and credit facilities (60% vs. 40%), which likely contribute to improved farming practices and market engagement. The average commercialization level for participants is 40.22%, compared to 34.52% for non-participants. Likewise, teff productivity is higher among participants, with an average yield of 11.88 Qt/ha compared to 10.51 Qt/ha for non-participants.

The comparison of mean values between teff farmers participating in cluster farming programs and those who do not reveals substantial differences in both productivity and commercialization. Productivity, measured in quintals per hectare, was significantly higher among participants, with an average of 11.88 Qt/ha, compared to 10.51 Qt/ha for non-participants. This results in a mean difference of 1.37 Qt/ha, indicating that participants outperformed non-participants by this margin. The statistical analysis shows a t-test value of -2.06**, which confirms that this difference is statistically significant at a moderate level.

In terms of commercialization, expressed as a percentage, participants in cluster farming programs also demonstrated a higher average at 40.22%, compared to 34.51% for non-participants. The mean difference is 5.71%, showing that participants had a significantly higher level of commercialization. The t-test result of -2.63*** indicates that this difference is statistically significant at a high level, providing strong evidence that participation in cluster farming positively influences commercialization. Overall, these findings suggest that involvement in cluster farming programs can lead to improvements in both productivity and commercialization among teff farmers.

Outcome variables	Total	NCLFP (104)	CLFP (N=92)	Mean diff.	t-test
	Mean (std. error)	**Mean (std. error)**	**Mean (std. error)**		
Productivity (Qt/ha)	11.16 (0.334)	10.51 (0.528)	11.88 (0.376)	-1.137	-2.06**
Commercialization level in percent	37.19 (1.096)	34.51 (1.399)	40.22 (1.67)	-5.7	-2.63***

Table 3: Comparison of Teff Productivity and Commercialization Among Two Groups Using T-Test

Own computation, 2021/22

Factors Affecting Teff Farmers Cluster Farming Participation

To estimate the propensity score for matching cluster farming participants (CLFP) with non-participants (NCLFP), a probit model is employed. This model calculates the propensity scores for each observation and predicts the conditional probability of participating in the cluster farming approach. The dependent variable is coded as 1 for CLFP participants and 0 for non-participants.

The survey results showed that approximately 46.94% of respondents were involved in cluster farming. The model's suitability and explanatory power were assessed, revealing that the likelihood function was significant (Wald $\chi 2$ = 48.92 with P < 0.000), indicating strong explanatory power..

The probit model results, presented in Table 4, highlight that several explanatory variables significantly influence participation in cluster farming. Notably, the age of the household head is a significant factor. The results indicate that an additional year of age decreases the likelihood of participating in cluster farming by 1%. This may be due to the intensive labor and communication required for new technologies and agronomic practices in cluster farming, which older farmers may be less inclined to adopt.

Interestingly, the educational level of respondents was found to negatively affect participation in cluster farming at a 5% significance level. An additional year of schooling reduces the likelihood of participation by 2.3%. This could be attributed to the increased confidence and independence of educated farmers, leading them to focus on off-farm activities and overlook the benefits of cluster farming.

Family size is positively associated with cluster farming participation at a 10% significance level. A larger family size increases the need for higher production to meet food requirements, making cluster farming an attractive option. The marginal effect shows that each additional family member increases the probability of participation by 6.5%. This is because larger families have more human resources and may be motivated to adopt new production technologies to meet their needs.

Access to credit plays a crucial role in encouraging farmers to participate in cluster farming. At a significant level, it enhances their likelihood of engagement by 25.3%, as shown by the marginal effects of the probit model. This is because credit boosts farmers' purchasing power for essential inputs like fertilizers and seeds, thereby facilitating their involvement in such farming practices. Moreover, meeting financial needs through credit can improve the overall well-being of farming households.

Income from off-farm and non-farm activities also significantly influences smallholder farmers' participation in cluster farming. The study found that having such income sources increases the probability of joining cluster farming by 32.8%. This diversification of income helps farmers accumulate capital for better seeds, technologies, and labor, ultimately enhancing their farming capabilities. The significance of off-farm activities was noted at a 5% level, highlighting their importance in supporting farmers' participation in cluster farming initiatives.

Explanatory variables	Coefficient (Std. error)	Marginal effect (Std. error)	Z-value	P-value
Sex of household head	-0.046 (0.217)	-0.018 (0.086)	-0.21	0.831
Age of household head	-0.032 (0.013)	-0.01 (0.005)	-2.39**	0.017
Educational of household head	-0.058 (0.028)	-0.023 (0. 011)	-2.02**	0.044
Family size households	0.165 (0.092)	0.065 (0.036)	1.80*	0.072
Cultivated land size	0.139 (0.109)	0.05 (0.043)	1.28	0.202
Tropical livestock unit	-0.014 (0.059)	-0.0.05 (0.043)	-0.23	0.816
Distance from nearest market	0.058 (0.061)	0.023 (0.023)	0.96	0.335
Membership to cooperative	0.32 (0.210)	0.126 (0.082)	1.53	0.123
Number of extension contact	0.027 (0.023)	0.01 (0. 009)	1.18	0.239
Accesses to credit	0.65 (0.207)	0.253 (0.078)	3.12***	0.001
Non /off farm income	0.85 (0.221)	0.328 (0.078)	3.86***	0.000
Constant	**-0.347 (0.217)**		**-0.39**	

Table 4: Factors Affecting Smallholder Teff Farmer's Participation to Cluster Farming

***, **, and * significant at 1, 5, and 10% probability level, respectively
Own computation, 2021/22

Estimating the Propensity Score

The propensity scores for cluster farming participants show a mean of approximately 0.59, with a standard deviation of about 0.21. The scores range from a minimum of 0.01 to a maximum of 0.97. This indicates a significant variation in the likelihood of participating in cluster farming among households.

In comparison, non-cluster farming participants have a lower mean propensity score of about 0.36, with a standard deviation of roughly 0.19. Their scores range from 0.04 to 0.86. When considering all households together, the mean propensity score is around 0.47, with a standard deviation of about 0.23, and a range from 0.01 to 0.97. This suggests that overall; there is a moderate level of propensity to participate in cluster farming across the population.

Propensity score	Mean	Std. deviation	Minimum	Maximum
Cluster farming participants	0.5947941	0.2104259	0.0123185	0.9739361
Non-cluster farming participants	0.3634536	0.1925138	0.0357639	0.8640437
Total households	0.472042	0.2315976	0.0123185	0.9739361

Table 5: Sample Households Estimated Propensity Score

Own computation, (2021/22)

Common Support Assessment

Researchers often determine the common support region between participants and non-participants after calculating propensity scores for teff cluster farming. Observations outside this range are excluded, while those within it are retained for further analysis. In this study, propensity scores ranged from 0 to 1, with the overall sample scoring between 0.0123185 and 0.9739361 and an average of 0.472042. Participants in cluster farming had scores from 0.0123185 to 0.9739361, averaging 0.5947941, whereas non-participants scored between 0.0357639 and 0.8640437 with a mean of 0.3634536. The common support region was defined by scores from 0.0357639 to 0.8640437, encompassing overlapping values for both groups.

Propensity Score Distribution

Propensity score distribution analysis is employed for comparing treatment and control households prior to matching and it help to determine whether the common support assumption is sufficiently satisfied to ensure valid matching between the two groups. The study used kernel density estimates (KDE) to determine propensity score distribution for cluster farming participants CLFP) with non-participants (NCLFP). The result indicates that most of CLFP households fell within common support region that only a small number of observations prevailing outside this range at either tail. On the other hand, all NCLFP households were lying within the common support region.

As depicted in Figures 2–4, CLFP farm households showed higher propensity scores, clustering around 0.6, whereas NCLFP farm households were about 0.35. This deviation is expected that the treatment group has higher predicted probabilities of participation. However, the common support region between these distributions shows adequate matching potential among two groups.

Observational studies outside the common support region were excluded from the matching exercise to ensure robustness of the impact analysis of the study. In this study, about 4.59% of the total CLFP household's fell outside the common support region and were therefore removed from the dataset. The remaining sampled farm households were used to estimate the effects of cluster farming participation on teff productivity (yield per hectare) and the of commercialization level.

Figures 2 to 4 indicates graphical information's of the pre-matching Kernel density distributions. Figure 2 shows the total density of propensity scores distribution before matching. Figures 3 and 4 depict the kernel density distributions separately for CLFP and NCLFP farm households. The overall assessment of matching from figure 2 to 4 shows the suitability of employing propensity score matching (PSM) to reduce selection bias and make credible counterfactuals.

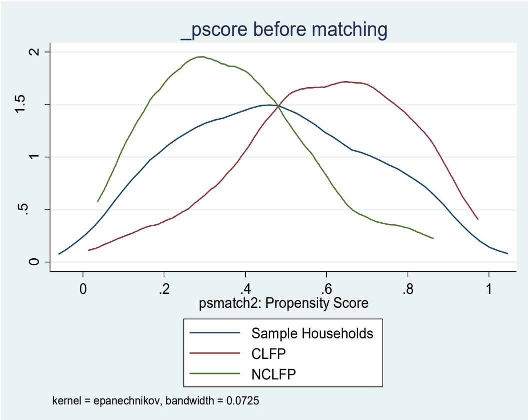

Figure 2: Density of Propensity Score Distribution Before Matching

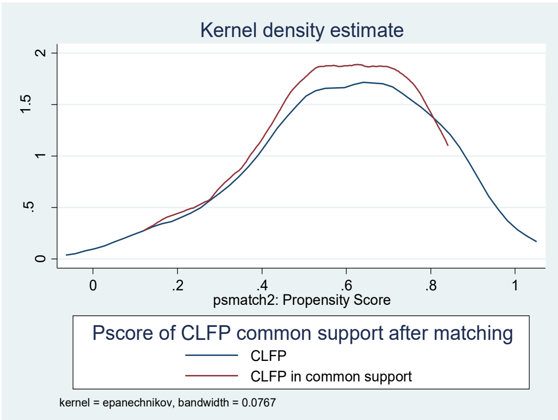

Figure 3: Kernel density of propensity scores of cluster farm participants (CLFP)

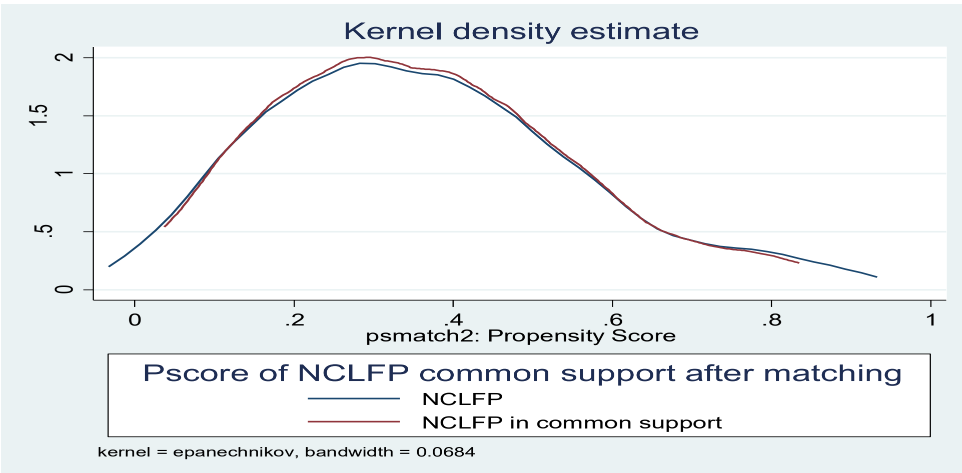

Figure 4: Kernel Density of Propensity Scores of Non-Cluster Farm Participants (NCFP)

Matching and Algorithm Choices

This study utilized alternative matching estimators to align the treatment and comparison groups within the common support region. The matching process relies on propensity scores and ensures that the distribution of relevant variables is balanced across both the control and treatment groups. According to Rosenbaum and Rubin (1983) and Caliendo and Kopeinig (2005), the choice of a matching estimator can be determined by criteria such as Pseudo-R2, standardized bias balancing tests, matched sample size, and T-tests.

The performance of various matching algorithms was evaluated using nearest neighbor matching, caliper matching, and kernel matching. The results, as shown in Table 6, indicate that nearest neighbor matching (with two neighbors) performed best. It achieved a large matched sample size, a low Pseudo-R2, a high number of insignificant variables (as indicated by insignificant T-tests post-matching), and a low mean standardized bias. Consequently, this algorithm was selected as it met all the specified criteria, and the study's findings are based on its outcomes.

To further validate the matching process, the mean absolute standardized bias method was employed, as recommended by Rosenbaum and Rubin (1983). This involves ensuring that the standardized difference is less than 20% to confirm successful matching. The mean bias after matching ranged from 7.8% to 14.6%, which is below the recommended threshold. Additionally, the T-values from the balancing test regression indicated no statistical difference in the mean of covariates between cluster farming participants and non-participants, confirming that all covariates were balanced post-matching.

Matching estimator	Psedo R^2 after matching	Number of insignificant variables after matching	Matched sample size	Mean Bias
Nearest neighbor matching				
Nearest neighbor 1	0.049	11	187	13.1
Nearest neighbor 2	**0.042**	**11**	**187**	**13.4**
Nearest neighbor 3	0.039	10	187	11.7
Nearest neighbor 4	0.037	10	187	11.7
Nearest neighbor 5	0.035	10	187	11.8
Caliper matching				
Radius 0.01	0.050	10	164	12.9
Radius 0.1	0.049	11	187	13.1
Radius 0.25	0.049	11	187	13.1
Radius 0.5	0.049	11	187	13.1
Kernel matching				
Bandwidth 0.01	0.048	10	164	14.6
Bandwidth 0.1	0.037	10	187	10.4
Bandwidth 0.25	0.03	10	187	8.8
Bandwidth 0.5	0.073	11	187	14.2

Table 6: Evaluating the Performance of Matching Algorithms

Source: own computation, 2021/22

Balancing Test of the Covariates After Matching

To ensure the effectiveness of the matching process, a balance check was conducted using propensity scores and covariates after applying the nearest neighbor matching algorithm. The results of these balance tests, both before and after matching, are summarized in Table 7. Firstly, the standardized differences in propensity scores and covariates ranged from -36.3% to 53.2%. However, after matching, these differences were significantly reduced, falling within the range of -23.6% to 23.3%. This reduction indicates a substantial improvement in balance between the groups.

The mean differences in individual covariates between participants and non-participants in cluster farming were also examined. It was found that these differences were less than 25%, which aligns with the criteria established by Rosenbaum and Rubin (1985). This suggests that the matching process effectively balanced the covariates between the two groups, thereby reducing potential biases.

Before the matching process, significant differences were observed between cluster farming participants and non-participants. Specifically, a t-test revealed that seven variables were statistically significant at a probability level of less than 5%. This indicated that the two groups were distinct in terms of certain characteristics. However, after matching, all variables showed statistically insignificant differences, demonstrating that the matching process successfully eliminated these initial disparities.

The successful creation of covariate balance between participants and non-participants supports the assumption that selection bias has been minimized. Consequently, it is reasonable to proceed with comparing the outcomes between cluster farming participants and non-participants. This comparison can now be made with confidence, particularly regarding mean yield and commercialization outcomes. The matching procedure has effectively established a basis for a fair and unbiased comparison between these groups.

Variable	Sample	Mean		Standardized bias		T- ratio	
		Treated	Control	% bias	% reduction	t-value	p>[t]
_p score	Unmatched	.59479	.59022	2.3	99.8	0.15	0.881
	Matched	.57457	.57402	0.3		0.02	0.985
Sex of HHH	Unmatched	.67391	.69231	-3.9		-0.28	0.784
	Matched	.6988	.6747	5.2	-31.0	0.33	0.740
Age of HHH	Unmatched	44.304	47.087	-36.3		-2.54	0.012
	Matched	44.928	43.139	23.3	35.7	1.46	0.148
Educational HHs	Unmatched	5.3043	6.4038	-31.5		-2.20	0.029
	Matched	5.5542	5.7831	-6.6	79.2	-0.43	0.668
Family size HHs	Unmatched	3.092	2.8125	23.8		1.67	0.097
	Matched	3.0586	2.9609	8.3	65.1	0.52	0.602
Cultivated land HHs	Unmatched	2.5435	2.2428	31.7		2.21	0.028
	Matched	2.5151	2.4443	7.5	76.5	0.47	0.640
Tropical livestock unit HHs	Unmatched	5.3252	5.5406	-12.9		-0.90	0.370
	Matched	5.3081	5.5952	-17.2	-33.3	-1.13	0.260
Market Distance	Unmatched	2.9652	2.8298	8.0		0.57	0.573
	Matched	2.9434	2.8542	5.3	34.2	0.33	0.738
Cooperative membership	Unmatched	.6087	.50962	20.0		1.39	0.165
	Matched	.60241	.48795	23.1	-15.5	1.48	0.140
Number of extension contact	Unmatched	10.761	9.4712	28.5		1.99	0.048
	Matched	10.614	10.114	11.0	61.2	0.67	0.506
Accesses to credit	Unmatched	.6087	.40385	41.6		2.91	0.004
	Matched	.59036	.51205	15.9	61.8	1.01	0.313
Off/non-farm income	Unmatched	.65217	.39423	53.2		3.71	0.000
	Matched	.62651	.74096	-23.6	55.6	-1.59	0.114

Table 7: Balancing Test of the Covariates After Matching

Source: Own survey, 2021/22

Impact of Cluster Farming on Teff Productivity

The analysis in Table 8 highlights the impact of teff cluster farming on productivity, measured in quintals per hectare (Qt/ha). The unmatched comparison indicates that farmers participating in cluster farming achieved a mean teff productivity of 11.887 Qt/ha, while non-participants recorded a lower average of 10.56 Qt/ha. This results in a productivity difference of 1.32 Qt/ha, which is statistically significant with a t-statistic of 1.99. These findings suggest that cluster farming contributes positively to teff productivity, even before accounting for other influencing factors.

When matched using the Average Treatment Effect on the Treated (ATT) approach, the results show an even greater impact. Cluster farming participants achieved an average productivity of 11.87 Qt/ha compared to 9.63 Qt/ha for non-participants, yielding a difference of 2.25 Qt/ha. This difference is statistically significant at 5% level, as indicated by the t-statistic of 2.31**. The matched results provide stronger evidence that cluster farming enhances teff productivity by addressing variations between treated and control groups.

Variables	Sample	Treated	Control	Difference	Std.error	T-stat
		Mean (qt/ha)	Mean (qt/ha)			
Teff productivity	Unmatched	11.887	10.56	1.32	0.664	1.99
	Matched (ATT)	11.887	9.63	2.25	1.154	1.69**

Table 8: Impact of Teff Cluster Farming on Teff Productivity (Qt/ha)

Own survey, 2021/22

Note: ** represent significance at 5% significance level.

Impact of Cluster Farming on Teff Commercialization

The impact of Teff cluster farming on commercialization levels is analyzed in Table 9. This table presents data on the commercialization level of Teff, expressed as a percentage, comparing treated and control groups. The data is further divided into unmatched and matched samples, with the latter using the Average Treatment Effect on the Treated (ATT) method.

In the unmatched sample, the mean commercialization level of Teff for the treated group is 40.2%, while it is 34.6% for the control group. This results in a difference of 5.6%. For the matched sample, the mean commercialization levels are 40.22% for the treated group and 33.8% for the control group, with a difference of 6.38%. The standard error and t-statistic are also provided to assess the statistical significance of these differences.

The statistical analysis indicates that the difference in commercialization levels between the treated and control groups is significant. Specifically, the matched sample shows a significance level of 10%. This suggests that the impact of teff cluster farming on commercialization is not only positive but also statistically significant, supporting the effectiveness of this farming approach in enhancing commercialization levels.

Variables	Sample	Treated	Control	Difference	Std.error	T-stat
		Mean	Mean			
Teff commercialization level in percent	Unmatched	40.22	34.61	5.6	0.021	2.58
	Matched (ATT)	40.22	33.83	6.38	0.026	2.31*

Table 9: Impact of Teff Cluster Farming on Commercialization Level (Percent)

Own survey, 2021/22

Note: * represent significance at 10% significance level.

Conclusions and Recommendation

Conclusions

Cluster farming has proven to be an effective approach for enhancing teff productivity and commercialization among smallholder farmers. Participants in cluster farming achieved higher average yields, with an increase of 2.25 qt/ha compared to non-participants, as measured through propensity score matching. Additionally, commercialization levels were significantly higher for participants, averaging 40% compared to 34% for non-participants, with a statistically significant difference at the 1% level. Socioeconomic factors such as age, education, family size, access to credit, and off/non-farm income played a critical role in influencing participation. While age and education negatively impacted participation decisions, larger family sizes, better credit access, and non-farm income positively encouraged involvement in cluster farming. This practice not only boosts productivity but also facilitates market integration and economic advancement for farmers.

Recommendations

To maximize the benefits of cluster farming, policymakers should prioritize expanding the number of participating farmers and increasing cultivated areas under this system. Scaling up cluster farming initiatives across diverse regions can significantly boost productivity and promote commercial agriculture. Addressing barriers such as age and education through tailored training programs and awareness campaigns is essential for encouraging broader participation.

Strengthening coordinated extension services, improving access to credit, and scaling the cluster farming model directly supports the Agricultural Commercialization Clusters (ACC) program's goals of enhancing smallholder productivity and market integration in Ethiopia. Lastly, conducting longitudinal studies using comprehensive data can offer deeper insights into the long-term impacts of cluster farming on productivity and commercialization, thereby informing future strategies and interventions.

• **Author Contributions:** The author was involved in the study's conception and design, data collection, statistical analysis, and manuscript drafting. The author took full responsibility for drafting and finalizing the manuscript.

• **Funding:** The author did not receive any specific funding for this work.

• **Competing Interests:** The author declares that there are no competing interests.

Questionnaire Preparation and Language Specifications

Questionnaires was prepared in English and subsequently translated into Amharic, the local working language in the study area. The translation was conducted through a standard forward backward translation procedure to ensure semantic and conceptual equivalence. A fluent expert translated the English version into Amharic and another second independent fluent expert then back-translated the Amharic version into English. Inconsistencies between the original and back translated versions were reviewed and resolved by the research team to ensure clarity and consistency. The final Amharic version was used for data collection.

- **Data Availability Statement:** Data is provided within the manuscript or supplementary information files.

- **Consent for Publication:** All participants provided consent for the publication of the study findings in journal articles.

Declarations

Ethics Approval and Consent to Participate

This study involved human participants (farmers) through interviews and survey questionnaires. The research protocol was reviewed and approved by the Wolkite University Institutional Review Board (IRB) in accordance with the guidelines and regulations outlined by the Ethiopian Ministry of Science and Higher Education. The Institutional Review Board (IRB) approval number is CANR-12-2021/22 and approved date was Jan 05/2021. We reviewed and aligned the manuscript with the CROSS guidelines for quantitative surveys and the COREQ guidelines for qualitative procedures.

All procedures performed in this study involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments. Prior to data collection, all participants were fully informed about the purpose and procedures of the research. Participation in the study was voluntary, and participants had the right to withdraw at any time without consequence.

Informed Consent

Written Informed Consent was obtained from all participants involved in this study. The objectives, risks, benefits, and confidentiality of their responses were clearly explained, and all participants voluntarily agreed to participate. In the case of participants who were unable to read or write, the information was read aloud and verbal Consent was Obtained and Witnessed. No data were collected from participants under the age of 16.

References

1. Akhmadeev, R., Redkin, A., Glubokova, N., Bykanova, O., Malakhova, L., & Rogov, A. (2019). Agro-industrial cluster: supporting the food security of the developing market economy. *Entrepreneurship and sustainability issues, 7*(2), 1149.
2. Getahun, A., & Milkias, D. (2021). Review on agricultural extension systems in Ethiopia: a cluster farming approaches. *J Biol Agric Healthc, 11*(14), 1-6.
3. Abate, S. (2021). *Impact of cluster farming on farmers productivity and commercialization: the case of Dera woreda* (Doctoral dissertation).
4. Karki, L., Shange, R., Hill, W. A., Bonsi, C., English, H., Agbodjan, E., ... & Idassi, J. (2021). Assessing the impact of cluster farming initiatives on small and socially disadvantaged farmers, ranchers, and forestland owners: a case of the southeastern region of the United States. *Professional Agricultural Workers Journal (PAWJ), 7*(2), 26-41.
5. Mamo, H., & Tagess, L. (2020). Gender Differential in Productivity and Income of Haricot Bean in Misrak Badawacho District of Southern Ethiopia. *Ethiopian Journal of Business and Social Sciences, 3*(1), 42-56.
6. Louhichi, K., Temursho, U., Colen, L., Paloma, S. G., Batt, P. J., & Murray-prior, R. (2019). Upscaling the productivity performance of the Agricultural Commercialization Cluster Initiative in Ethiopia. *JRC Science for Policy Report, Publications office of the European Union, Luxembourg.*
7. Haji, P. (2019). *Production efficiency, commercialization and its impact on food security of smallholder pulse producers in east Gojjam zone, Amhara region, Ethiopia* (Doctoral dissertation, Haramaya university).
8. Gollin, D. (2018). Structural transformation and growth without industrialisation. *Background Paper. Oxford: Pathways for Prosperity Commission.*
9. Dureti, G. G., & Tabe-Ojong, M. P. J. (2024). Land as a binding constraint to cluster-based development in Ethiopia: To cluster or not to cluster?. *Plos one, 19*(4), e0298784.
10. Degefu, S., Sileshi, M., & Ogeto, M. A. (2024). Impact of cluster farming on wheat productivity and net benefit among smallholder farmers in Lemu-Bilbilo and Hetosa districts of Arsi Zone, Ethiopia. *Discover Food, 4*(1), 59.
11. Habtewold, A. B., & Challa, T. M. (2019). Challenges and opportunities for smallholder farmers participation in teff market in Ambo District, West Shoa Zone of Oromia, Ethiopia. *International Journal of Business and Social Science, 10*(8), 42-48.
12. Tefera, G. N., Aredo, M. K., Nejo, Z. S., & Ibrahim, K. J. (2023). Impact of wheat cluster farming practice on smallholder's asset building in Arsi zone of Ethiopia. *Journal of Business and Economic Development, 8*(1), 1-11.
13. Dureti, G. G., Tabe-Ojong, M. P. J., & Owusu-Sekyere, E. (2023). The new normal? Cluster farming and smallholder commercialization in Ethiopia. *Agricultural Economics, 54*(6), 900-920.
14. Milkias, D., & Beri, G. (2024). Factors influencing participation decision of smallholder farmers on cluster farming: the case of wheat technologies in Dawoo District, South-West Shewa Zone, Oromia Region, Ethiopia. *Middle East Res J Econ Manag, 4*(01), 1-7.

15. Ali, A. B., & Tefera, T. L. (2024). The Nexus between Cluster Farming and Household Dietary Diversity among Smallholder Wheat Farmers in Ethiopia. *Turkish Journal of Agriculture-Food Science and Technology, 12*(10), 1753-1761.
16. Sultan, O. (2024). Analysis of factors affecting participation of smallholder farmers in wheat cluster farming: the case of Gasera District, bale zone, Oromia region, Ethiopia. *Plant, 12*(4), 88-103.
17. Massresha, S. E., Lema, T. Z., Neway, M. M., & Degu, W. A. (2021). Perception and determinants of agricultural technology adoption in north shoa zone, Amhara regional state, Ethiopia. *Cogent Economics & Finance, 9*(1), 1956774.
18. Getahun, A., Assefa, C., & Dereje, G. (2023). Effects of cluster farming and crop technology dissemination on the livelihoods of farmers: The case Chobi District West Shewa Zone of Oromia, Ethiopia. *Middle East Research Journal of Agriculture and Food Science, 3,* 57-61.
19. Seifu, M., van Paassen, A., Klerkx, L., & Leeuwis, C. (2022). A state-initiated multi-stakeholder platform as an instrument to build agricultural innovation system capacity: a case study from Ethiopia. *Innovation and Development,* 1-22.
20. Mekonnen, A., Tamrat, M., Hunduma, S., Dinkecha, K., & Shiferaw, T. (2025). Optimizing Nitrogen Fertilization for Improved Barley Production in the Central Highlands of Ethiopia. *Results of Crop Improvement and Management Research for 2023.*
21. Maddala, G. S. (1983). *Limited-dependent and qualitative variables in econometrics* (No. 3). Cambridge university press.
22. Lokshin, M., & Sajaia, Z. (2004). Maximum likelihood estimation of endogenous switching regression models. *The Stata Journal, 4*(3), 282-289.
23. Angrist, J. D., & Pischke, J. S. (2009). *Mostly harmless econometrics: An empiricist's companion*. Princeton university press.
24. Xu, Y. (2017). Generalized synthetic control method: Causal inference with interactive fixed effects models. *Political Analysis, 25*(1), 57-76.
25. 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.
26. Caliendo, M., & Kopeinig, S. (2008). Some practical guidance for the implementation of propensity score matching. *Journal of economic surveys, 22*(1), 31-72.
27. Lechner, M., & Strittmatter, A. (2019). Practical procedures to deal with common support problems in matching estimation. *Econometric Reviews, 38*(2), 193-207.
28. Sodo District Office of Agriculture. (2022). Annual Agricultural Report. East Guraghe Zone, Ethiopia.
29. Yamane, S . The formula for sample size determination of households, 1967.
30. Endalew, B., Elias, A., & Yasunobu, K. (2024). Impact of cluster farming on smallholder farmers teff commercialization in Ethiopia. *CABI Agriculture and Bioscience, 5*(1), 18.
31. Sida, A., Tessema, A., & Shibabaw, K. (2021). Determinants of Smallholder Crop Commercialization: The Case of Agarfa and Sinana Districts of Bale Zone, Southeastern Ethiopia.
32. Ababa, A. (2021). LANDSCAPE ACTION PLAN FOR SODO AND SODO GURAGIE WOREDAS, SNNP REGIONAL STATE.
33. Eyasu, A. M., Zewotir, T., & Dessie, Z. G. (2025). Impact of crop commercialization on multidimensional poverty in rural Ethiopia: propensity score approach. *Frontiers in Public Health, 12,* 1412670.
34. Getahun, A. (2020). Smallholder farmers agricultural commercialization in Ethiopia: A review. *Agriculture, Forestry and Fisheries, 9*(3), 67.
35. Gidelew, G. E., Alemu, B. A., & Kassie, K. E. (2025). The crop commercialization impact of cluster farming initiative in Northwestern Ethiopia. *Frontiers in Sustainable Food Systems, 9*, 1548304.
36. Mekonnen, K., Yasabu, S., Gebremedhin, B., Woldemeskel, E., Tegegne, A., & Thorne, P. J. (2019). Promoting productivity and market access technologies and approaches to improve farm income and livelihoods in Ethiopia: Lessons from action research projects.
37. Carvalho, C. D. O. (2018). Women, business and the law 2018.