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# Impact of cluster farming on smallholder farmers teff commercialization in Ethiopia

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## Abstract

**Background** Cluster farming is an agricultural practice that involves organizing and grouping together farmers within a specific geographic area based on proximity of their farm plots to create synergies and economies of scale. In developing countries including Ethiopia cluster farming has gained prominence as a strategic initiative to foster commercialized agriculture and enhance the livelihoods of smallholder farmers by integrating their production within the broader value chain. In light of this, the government of Ethiopia plans to promote cluster farming throughout the country based on the best practices of the four cluster farming priority regions and 10 high-value commodities. Teff is one of the high-value commodities in the cluster farming priority regions. However, the impact of cluster farming on teff commercialization was not studied before.

**Methods** We conducted this study to examine the impact of cluster farming on teff commercialization using nationally representative data collected by Agricultural Transformation Institute of Ethiopia. Then, we analyzed the data using descriptive and inferential statistics, commercialization index, and endogenous switching regression model.

**Results** The result revealed that the mean teff commercialization of cluster farming participants was higher than non-participants in all the cluster farming priority regions of Ethiopia. Similarly, the model result indicated that cluster farming had a positive and significant impact on teff commercialization at $p < 0.01$.

**Conclusion** The findings suggest that the promotion of cluster farming facilitates teff commercialization in Ethiopia. However, we recommend further studies using panel data collected from large samples to provide a longitudinal perspective on the impact of cluster farming on teff commercialization over time. The findings of these studies can offer comprehensive insights and concrete information that can inform policymakers to support and promote teff cluster farming in Ethiopia.

**Keywords** Cluster farming,, Endogenous switching regression, Ethiopia, Household commercialization index, Teff

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## Introduction

Agriculture contributes significantly to the economies of both developed and developing countries (Praburaj et al. 2019). It has a central role in the lives of numerous individuals across the globe (Alston and Pardey 2014). But agricultural production is dominated by smallholders both in developing and developed countries (International Finance Corporation 2016; Rapsomanikis 2015). However, smallholder farmers are extremely poor (World Bank 2008). Their deprivation is directly related to their employment in the agriculture sector (FAO 2012). As Pingali (1997) emphasized, it is impossible to reduce poverty through subsistence agriculture. Therefore, improving agricultural productivity is the most effective strategy for reducing the prevalence of chronic poverty (Syed and Miyazako 2013). As discussed by Schulte et al. (2023), an increase in commercialization level also reduces multidimensional poverty of farmers. Accordingly, World Bank (2012) suggested a cluster-based approach to enhance agricultural productivity to reduce poverty. A cluster approach is a sustainable farming practice to transform subsistence crop production into a market-based production system (Otsuka and Ali 2020). As a result, agricultural clusters are popular both in developed and developing countries to improve productivity, commercialization and income of farmers (Galvez-Nogales 2010; Ping and Koziol 2011; Rasulov et al. 2020).

In Ethiopia, agricultural production is dominated by subsistent and smallholder farmers (Boere et al. 2016; Getahun 2020). As a result, smallholder commercialization is a driving force to transform subsistence agriculture in Ethiopia (Getahun 2020). The government of Ethiopia is striving to improve smallholder farmer's productivity and commercialization. Accordingly, different development interventions have been launched to realize the commercialization of smallholder agriculture. Thus, cluster farming is the main agricultural development intervention that has several advantages in transforming traditional agriculture through vertical and horizontal linkages with value chain actors (ATA 2015; Endaznow 2020; Mamo 2019). It focuses on sustainable increases in productivity and profitability of smallholder farmers to improve their livelihoods (ATA 2019b). As a result, improved access to market is one of the outcomes of cluster farming to enhance smallholder farmers' livelihoods through a market-oriented production system (Tafesse 2022). Consequently, high-value commodities are targeted by cluster farming to transform subsistent production to market driven production through market linkages with value chain actors in the four cluster farming priority regions of Ethiopia such as Amhara, Oromia, Southern Nations, Nationalities and People's (SNNP) and Tigray (Abate 2021; Louhichi et al. 2019; Pauw 2017). As a result, approximately 3.05 million quintals of high-value commodities (sesame, maize, wheat, malt barley and teff) were sold through contracts signed between farmers and value chain actors in the 2020/21production season (ATA 2021).

Moreover, Louhichi et al. (2019) added that the clusters of the four regions serve as models for learning areas to scale up best practices across the country. Hence, the government of Ethiopia has a plan to scale up cluster farming throughout the country based on the best practices of the cluster farming priority regions and 10 high-value commodities to commercialize smallholder dominated agricultural production. Teff is one of the high-value commodities in the cluster farming priority regions of Ethiopia. As a result, a total of 204,885 smallholder farmers cultivated teff through cluster farming on 83,055 hectares of land during the 2019/20 production season (Getahun and Milkias 2021). However, the commercialization level of teff cluster farming and the impact of cluster farming on teff commercialization were not documented in reports and scientific papers. Thus, empirical studies that support the government's plan to promote teff cluster farming throughout the country are rare. For instance, Abate (2021) examined the impact of cluster farming on maize commercialization in Ethiopia using a propensity score matching model. Similarly, Jr Tabe-Ojong and Dureti (2023) investigated the impact of cluster farming on household poverty using an instrumental variable model. However, propensity score matching, and instrumental variable models do not capture selection bias that arises because of observed and unobserved heterogeneities (Alene and Manyong 2007; Shiferaw et al. 2014; White and Raitzer 2017), which results in underestimation or overestimation of the impact results (Alene and Manyong 2007; Jaleta et al. 2015). For instance, studies by Kassie et al. (2009) and Elias et al. (2013) underscored the existence of serious selection bias in the adoption of improved farming practices and participation in the national agricultural extension program in Ethiopia. Thus, due to selection bias, the previous cluster farming studies (Abate 2021; Tabe-Ojong and Dureti 2023) might not provide tangible evidence for policy makers and stakeholders. Furthermore, the study by Dureti et al. (2023) investigated the impact of cluster farming on commercialization of high-value commodities in Ethiopia. The study found that landholding is the main source of heterogeneity of commercialization in cluster farming. However, commercialization is affected by socioeconomic variables (age, sex, educational status, household size, on-farm income and off-farm income participation) and plot characteristics (landholding) (Anteneh and Endalew 2023; Endalew et al. 2020; Getahun et al. 2019; Gidelew et al. 2022; Jaleta et al. 2009; Sida et al. 2021; Tabe-Ojong et al. 2022). Consequently, landholding is one but not the only source of heterogeneity in commercialization. Therefore, the exclusion of additional sources of heterogeneity leads to underestimation or overestimation of the impact of cluster farming on commercialization. Therefore, we included socio-economic variables and plot characteristics in the analysis to comprehensively account potential sources of heterogeneity and provide a more accurate prediction of the impact of cluster farming on teff commercialization. Specifically, how teff commercialization looks like in the cluster farming priority regions of Ethiopia, what factors

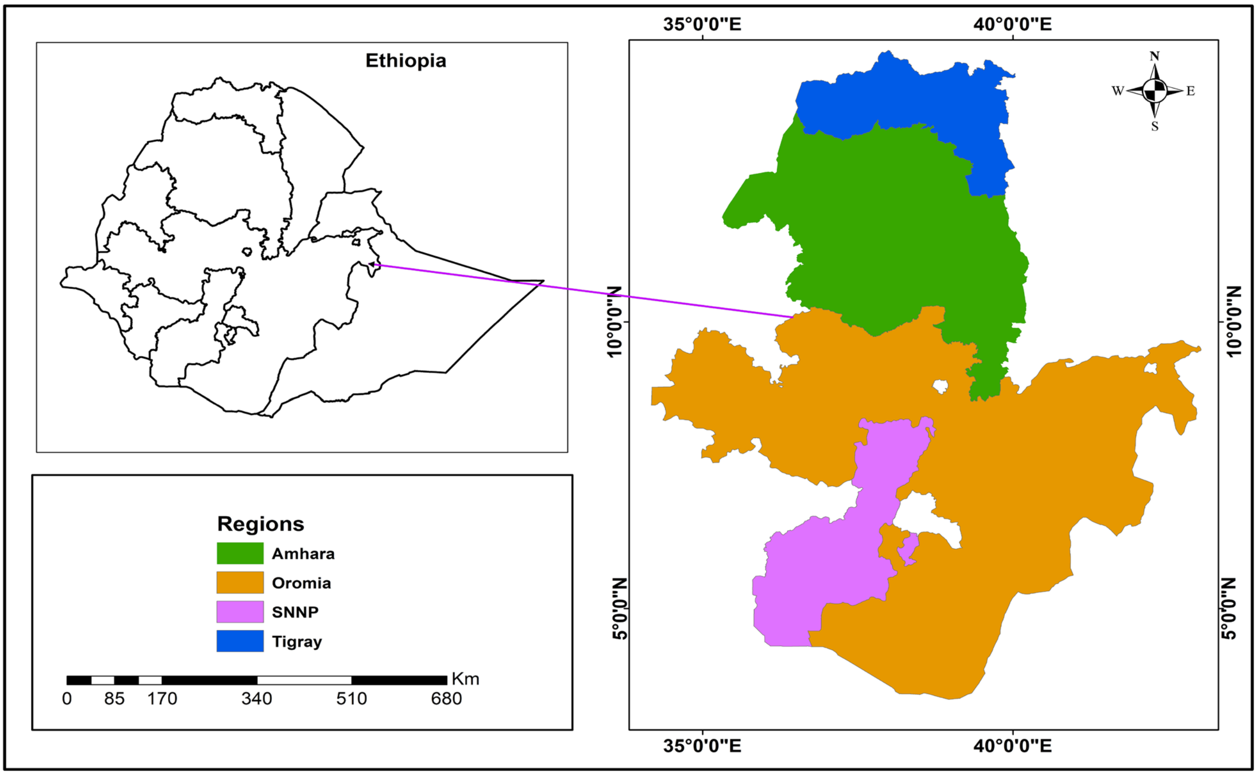


**Fig. 1** Map of the cluster farming priority regions and study area

influence farmers' participation in teff cluster farming and does participation in cluster farming have a positive impact on teff commercialization were not studied at national, regional, and household levels. Consequently, this study was carried out to answer the aforementioned research questions using data collected from the four priority regions in Ethiopia, where cluster farming is actively implemented.

## Materials and methods

### Data sources and sampling procedure

We used the survey data collected by Agricultural Transformation Institute (ATI) of Ethiopia in 2019. The data were collected using a multistage random sampling procedure from four cluster farming priority regions (Fig. 1), 37 districts, 587 kebeles,[1] and 1,876 smallholder farmers who cultivate five high-value commodities: maize, wheat, teff, malt barley, and sesame. During the data collection process, serious attention was paid to improving data quality through a timely check-up technique. The entire data collection process was also supervised and managed by ATI[2] of Ethiopia. Thus, this study used a total of 290 smallholder teff producers' data extracted from the 1876 observations to address objectives of this study (Table 1). Data cross checking was made to select potential variables for this study. Accordingly, we excluded two variables due to missing observations (access to credit) and insufficient variation in responses (access to extension service). Finally, sex of respondents, age of respondents, educational status, household size, landholding, on-farm

**Table 1** Sample size distribution by region and cluster farming participation

| Region | Cluster farming participation | | Total |
|---|---|---|---|
| | Participant | Non-participant | |
| Amhara | 35 | 22 | 57 |
| Oromia | 97 | 47 | 144 |
| SNNP | 31 | 21 | 52 |
| Tigray | 17 | 20 | 37 |
| Total | 180 | 110 | 290 |

[1] Kebele is the smallest administrative structure in Ethiopia.

[2] ATI is a public sector institution established to transform the agriculture sector by introducing viable interventions like cluster farming.

income, off-farm income participation, access to teff storage, participation of neighbors in cluster farming and membership in social groups were selected and incorporated in the descriptive statistics and econometric models to accomplish objectives of this study. The volume of teff production, teff marketed surplus and market price of teff were also selected and used to compute teff commercialization index for each observation.

### Methods of data analysis

#### *Descriptive and inferential statistics*

Descriptive statistics such as mean and standard deviation were used to encapsulate the findings of this study. An independent t-test was also applied to measure the presence of a significant mean teff commercialization difference between cluster farming participants and non-participants. Additionally, we used f-test to compare the average teff commercialization difference among the cluster farming priority regions. Moreover, the Bonferroni test was employed to confirm the presence of significant mean teff commercialization difference within the regions.

#### *Measurement of teff commercialization*

In the existing literature, agricultural commercialization is often measured using the Household Commercialization Index (HCI). Accordingly, various authors have applied HCI to measure commercialization level of farm households (Getahun 2020; Getahun et al. 2019; Gidelew et al. 2022; Jaleta et al. 2009; Leta 2018; Sida et al. 2021; Strasberg et al. 1999). Therefore, we used the same method to measure teff commercialization in the cluster farming priority regions of Ethiopia, and HCI is calculated as follows.

$$HCI_i = \frac{\text{Value of teff sales in market}}{\text{Teff production value}} \tag{1}$$

where $HCI_i$ is the household commercialization index of the $i^{th}$ farmer. It ranges from 0 (fully subsistence) to 1 (fully commercialized). The $HCI_i$ value close to 1 indicates that the majority of each farmer's production is sold in the output market (Birhanu et al. 2021). Therefore, we computed the teff commercialization index to provide adequate information about the participation of teff producers in the output market.

#### *Econometric model*

Various econometric models are available to measure the impact of development interventions on outcome variables (Khandker et al. 2009; White and Raitzer 2017). For example, propensity score matching, and instrumental variable econometric models are frequently used in the existing impact evaluation literatures (Abate 2021; Ndlovu et al. 2022; Otieno et al. 2022; Salam and Sarker 2023; Tadesse and Tariku 2022; Zhang et al. 2023). However, propensity score matching only captures the observed variation (Shiferaw et al. 2014; White and Raitzer 2017), while instrumental variable model considers unobserved differences (Shiferaw et al. 2014). However, the treatment variable is affected by both the observed and unobserved variation, which leads to a self-selection bias (Alene and Manyong 2007; Shiferaw et al. 2014). Thus, the impact of the intervention program on the outcome variable is overestimated or underestimated due to selection bias (Alene and Manyong 2007; Jaleta et al. 2015). Consequently, various studies have applied an endogenous switching regression (ESR) model to capture selection bias that arises because of observed and unobserved factors (Jaleta et al. 2015; Kassie et al. 2009; Shiferaw et al. 2014; White and Raitzer 2017). According to Kassie et al. (2009), an ESR model follows a two-stage estimation procedure. However, the two-stage estimation procedure produces inconsistent standard error (Alene and Manyong 2007; Lokshin and Sajaia 2004). Accordingly, Lokshin and Sajaia (2004) developed the *movestay* command to estimate both binary and continuous models simultaneously to solve the problem of inconsistent standard error in the two-stage ESR model. Therefore, we employed the *movestay* command to estimate the impact of cluster farming on teff commercialization. We specified the model mathematically based on Lokshin and Sajaia (2004) as follows:

$$P_i^* = Z_i\alpha + \mu_i \quad \text{where} \quad P_i = \begin{cases} 1\, if\ Z_i\alpha + \mu_i > 0 \\ 0\, if\ Z_i\alpha + \mu_i \le 0 \end{cases} \tag{2}$$

where: $P_i$ and $P_i^*$ denote the decision to participate in the teff cluster farming and latent variable, $Z_i$ stands for explanatory variables that affect cluster farming participation decision (Table 2) and α and $\mu_i$ are the coefficient of the variables and the error term, respectively.

Then, the outcome equation (commercialization) was specified as follows:

$$\text{Regime 1}: \ C_{1i} = X_{1i}\beta_1 + \varepsilon_{1i} if\ Z_i\alpha + \mu_i > 0 \tag{3}$$

$$\text{Regime 2}: \ C_{2i} = X_{2i}\beta_2 + \varepsilon_{2i}\ if\ Z_i\alpha + \mu_i \le 0 \tag{4}$$

where: $C_1$ and $C_2$ are teff commercialization level of cluster farming participants and non-participants, Xi stands for explanatory variables in the outcome equation (Table 2),

$\beta_1 and \beta_2$ are coefficients of explanatory variables and $\epsilon_{1i}$ and $\epsilon_{2i}$ are error terms in the outcome equation.

Finally, we estimated the conditional expectations using the following formula (Lokshin and Sajaia 2004).

**Table 2** Descriptive statistics results and expected signs of independent variables

| Variables and their definitions | Total sample (N = 290) | Cluster farming participation | | Expected sign | |
|---|---|---|---|---|---|
| | | Participant (N = 180) | Non-participant (N = 110) | Cluster farming participation | Commercialization level |
| | Mean (SD) | Mean (SD) | Mean (SD) | | |
| Sex of respondents (1 if male, 0 otherwise) | 0.97 (0.17) | 0.97 (0.18) | 0.97 (0.16) | + | + |
| Educational status (1 if literate, 0 otherwise) | 0.63 (0.48) | 0.72 (0.45) | 0.47 (0.50) | + | + |
| Age (Years) | 43.96 (10.83) | 42.46 (10.48) | 46.40 (11.00) | – | – |
| Household size (Number) | 6.53 (2.39) | 6.30 (2.46) | 6.92 (2.23) | + | + |
| Landholding (Hectare) | 2.28 (1.54) | 2.55 (1.56) | 1.85 (1.40) | + | + |
| On-farm income (Ethiopian Birr) | 49523.29 (44618.34) | 56807.95 (47987.64) | 37602.95 (35575.75) | + | + |
| Off-farm income participation (1if yes, 0 otherwise) | 0.42 (0.50) | 0.43 (0.50) | 0.41 (0.49) | + | + |
| Access to teff storage (1 if yes, 0 otherwise) | 0.68 (0.47) | 0.77 (0.42) | 0.54 (0.50) | + | + |
| Neighbor participation in cluster farming (1if yes, 0 otherwise) | 0.19 (0.39) | 0.19 (0.40) | 0.17 (0.38) | | + |
| Membership in social group (1 if yes, 0 otherwise) | 0.41 (0.49) | 0.59 (0.49) | 0.81 (0.39) | + | |
| Amhara region (1if Amhara, 0 otherwise) | 0.20 (0.40) | 0.19 (0.40) | 0.20 (0.40) | + | + |
| Oromia region (1if Oromia, 0 otherwise) | 0.50 (0.50) | 0.54 (0.50) | 0.43 (0.50) | + | + |
| SNNP region (1if SNNP, 0 otherwise) | 0.18 (0.38) | 0.17 (0.38) | 0.19(0.39) | + | + |
| Tigray region (1if Tigray, 0 otherwise) | 0.13 (0.33) | 0.09 (0.29) | 0.18 (0.39) | Base | Base |
| Cluster farming participation (1 if participant, 0 otherwise) | 0.62 (0.49) | | | | + |

*SD* Standard deviation

$$E\left(C_{1i}|P_i = 1, X_{1i}\right) = X_{1i}\beta_1 + \sigma_1\rho_1 f(\alpha Z_i)/F(\alpha Z_i) \tag{5}$$

$$E\left(C_{1i}|P_i = 0, X_{1i}\right) = X_{1i}\beta_1 - \sigma_1\rho_1 f(\alpha Z_i)/[1 - F(\alpha Z_i)] \tag{6}$$

$$E\left(C_{2i}|P_i = 1, X_{2i}\right) = X_{2i}\beta_2 + \sigma_2\rho_2 f(\alpha Z_i)/F(\alpha Z_i) \tag{7}$$

$$E\left(C_{2i}|P_i = 0, X_{2i}\right) = X_{2i}\beta_2 - \sigma_2\rho_2 f(\alpha Z_i)/[1 - F(\alpha Z_i)] \tag{8}$$

where: $\rho_1$ and $\rho_2$ are correlation coefficients of error terms. The $\sigma_1$ and $\sigma_2$ represent covariances of error terms and F(.) and f(.) denote the cumulative distribution and normal density functions, respectively.

Therefore, the average treatment effects of the treated (ATT) and untreated (ATU) were computed applying the following formula:

$$ATT = E(C_{1i}|P_i = 1, X_{1i}) - E(C_{2i}|P_i = 1, X_{2i}) \tag{9}$$

$$ATU = E(C_{1i}|P_i = 0, X_{1i}) - E(C_{2i}|P_i = 0, X_{2i}) \tag{10}$$

Inverse probability weighted regression adjustment (IPWRA) is an impact evaluation model when we have confounding factors (Caldera 2019; Słoczyński et al. 2022). It is used to estimate the average treatment effect by controlling the selection bias arising from the observed factors (Zheng and Ma 2022 and 2023). In addition, the studies by Abate (2021) and Sawadogo et al. (2023) used an IPWRA model to check the robustness of the propensity score matching and the multinomial endogenous switching regression model. Therefore, IPWRA model was employed to confirm the robustness of the ESR model results. The ESR model could not generate marginal effect results. As a result, we employed a binary probit model to predict marginal effects of explanatory variables.

**Table 3** Comparison of teff commercialization level between cluster farming participants and non-participants using T-test

| Observation | Mean | Standard deviation |
|---|---|---|
| Total sample (N = 290) | 0.52 | 0.25 |
| Cluster farming participants (N = 180) | 0.57 | 0.23 |
| Cluster farming non-participants (N = 110) | 0.44 | 0.27 |
| T-test | 4.56*** | |

*** represents significance level at $p < 0.01$

## Results and discussion

### Descriptive statistics result

Table 2 depicts the descriptive statistics of the independent variables included in the ESR, IPWRA and binary probit models. The majority of sample respondents (97%) were male headed. Moreover, about 63% of sample respondents were literate, of which 72% participated in teff cluster farming. The average age of sample respondents was 44 years. Cluster farming participants had younger household heads (42.46 years) than non-participants (46.40 years). The average household size of the total observation was 6.53. The average household size of participants (6.30) was less than non- participants (6.92). Whereas the average landholding (2.55 ha) and on-farm income (56,807.95 Ethiopian Birr) of participants were greater than the average landholding (1.85 ha) and on-farm income (37,602.95 Ethiopian Birr) of non-participants. The participation of cluster farming participants (43%) in off-farm activities was higher than non-participants (41%). The results revealed that 68% of the respondents had access to teff storage. However, non-participants had less access to teff storage (54%) than participants (77%). Likewise, most of the participants and non-participants' neighbors did not participate in teff cluster farming. Conversely, most participants in cluster farming were non-members of social groups (41%) as compared to non-participants (19%).

### Teff commercialization level in cluster farming priority regions of Ethiopia

The mean teff commercialization for the total observation was 0.52. The mean commercialization of cluster farming participants (0.57) was higher than non-participants (0.44) (Table 3). This implies that about 57% and 44% of the total teff production was sold by the cluster farming participants and non-participants, respectively. This finding aligns with Dureti et al. (2023), who reported that about 56% of the cluster farming high-value commodities are sold to the market. Besides, cluster farming participants and non-participants used about 43% and 56% of their teff production for consumption and seed. We found a statistically significant mean commercialization difference between cluster farming participants and non-participants at $p < 0.01$. Likewise, the mean commercialization of cluster farming participants was higher than the national teff commercialization level reported in 2020 (0.30) and 2021 (0.35) production years (CSA 2020 and 2021). This illustrates that cluster farming is a promising farming practice to improve the commercialization level of participants.

Moreover, we investigated the mean teff commercialization difference among cluster farming priority regions. As shown in Table 4, the mean teff commercialization of Amhara region was higher than the rest of cluster farming priority regions. The Oromia region had a higher mean teff commercialization next to Amhara region. On the contrary, Tigray region was the lowest region in terms of teff commercialization among the cluster farming priority regions. As we confirmed using the F-test, the mean teff commercialization difference among cluster farming priority regions was significant at $p < 0.01$. We also found that farmers who participated in cluster farming had a higher mean teff commercialization than non-participants across all the priority regions. Besides, we compared the mean teff commercialization difference between regions using Bonferroni test (Table 5). The mean commercialization difference between SNNP and Amhara Region was negative and significant at $p < 0.01$. We also found a negative and significant mean teff commercialization difference between the Tigray and Amhara, as well as between the SNNP and Oromia, and between the Tigray and Oromia regions. Finally, all the mean differences were significant at $p < 0.01$. Therefore, the test result confirmed that Amhara and Tigray regions were the highest and lowest performing regions

**Table 4** Comparison of teff commercialization among cluster farming priority regions in Ethiopia using F-test

| Observation | Cluster farming priority regions | | | | F-test |
|---|---|---|---|---|---|
| | Amhara | Oromia | SNNP | Tigray | |
| Total sample | 0.64 | 0.58 | 0.44 | 0.25 | 30.71*** |
| Cluster farming participants | 0.66 | 0.60 | 0.49 | 0.36 | 9.81*** |
| Cluster farming non-participants | 0.60 | 0.53 | 0.34 | 0.15 | 20.15*** |

*** represents significance level at $p < 0.01$

**Table 5** Comparison of teff commercialization between cluster farming priority regions in Ethiopia using Bonferroni-test

| Mean difference[a] | Amhara | Oromia | SNNP |
|---|---|---|---|
| Oromia | −0.06 | | |
| SNNP | −0.21*** | −0.15*** | |
| Tigray | −0.39*** | −0.33*** | −0.19*** |

[a] Row mean minus column mean of teff commercialization level between regi

*** represents significance level at $p < 0.01$

respectively in terms of teff commercialization through cluster farming. The Amhara region is a larger producer and supplier of teff than the Tigray region because it has different agroecological and edaphic factors conducive to teff production. As reported by CSA (2021), the total teff production of Amhara region (20.96 million quintals) was higher than Tigray region (0.38 million quintals). This finding is in line with the real differences that can be observed between the Amhara and Tigray regions.

### Endogenous switching regression model results

We tested the independence of the two equations using a log-likelihood ratio test to confirm whether a one-stage ESR is appropriate or not. Therefore, we rejected the null hypothesis i.e., H0: $\rho_1=\rho_2= 0$ based on the test result. The result shows that the two equations are interdependent (Lokshin and Sajaia 2004 and 2011). Thus, the one-step ESR model is well fitted to estimate the continuous and decision variable simultaneously.

### Determinants of teff cluster farming participation in Ethiopia

As depicted in Table 6, teff cluster farming participation is affected by numerous factors. For example, educational status positively and significantly associated with teff cluster farming participation at $p < 0.01$. Thus, literate farmers are more likely to participate in teff cluster farming than illiterates. The likelihood of cluster farming participation increases by 27.2% if the head of the household is literate. This finding aligns with antecedent studies (Abate 2021; Checco et al. 2023), which reported that literate farmers are more aware of cluster farming information sources, extension programs and services, and yield-enhancing practices than illiterate farmers. Accordingly, literate farmers make informed decisions about participation in cluster farming to increase their productivity and profitability.

Conversely, the age of respondents negatively and significantly associated with teff cluster farming participation at $p < 0.1$. Therefore, a unit increase in the age of the respondent decreases the likelihood of teff cluster farming participation by 0.8%. This finding is in consonance with the results of Elias et al. (2013) and Kebede and Keba (2020) who found that the likelihood of adopting improved agricultural technology and practice decreases with each unit increase in the age of the respondent. Besides, teff production is a labor-intensive activity compared to other crops and this challenges older farmers to access sufficient labor during peak production periods.

On-farm income exhibited a positive and statistically significant association with teff cluster farming participation at $p < 0.01$. The likelihood of teff cluster farming participation rises by 17.3% for a unit increase in respondents' on-farm income. This might be due to farmers who have more income can buy more inputs and hire mechanized farming to meet the minimum production and productivity requirements of cluster farming. Consistent with this finding, the study conducted by Kebede and Keba (2020) found that the probability of adopting improved teff technologies increases as on-farm income increases. Similarly, off-farm income participation positively and significantly correlated with teff cluster farming participation at $p < 0.05$. The probability of teff cluster farming participation increases by 17.2% if the household head or household members are engaged in off-farm income activities. Thus, farmers involved in off-farm income- activities participate in teff cluster farming more than its counterpart. According to Mwangi and Kariuki (2015), off-farm income supplements rural households' income to overcome financial constraints in agricultural production and marketing processes. Moreover, previous studies depicted that off-farm income participation increases the likelihood of cluster farming participation and adoption of improved agricultural technology (Abate 2021).

Conversely, membership in social groups exhibited a negative and statistically significant relationship with teff cluster farming participation at $p < 0.01$. Thus, the likelihood of cluster farming participation decreases by 67% if the respondent is members of a social group. This implies that social group members participate less in teff cluster farming than non-members. However this result is in contrast with findings made by Mwangi and Kariuki (2015), which stated that social groups strengthen farmers' interaction, cooperation, information sharing and social networks. Conversely, Wardhana et al. (2021) argued that high competition pressure increases selfishness behavior of farmers because they believe self-interest will benefit them more than interaction with other farmers. This may explain the inverse relationship between social group membership and cluster farming participation. Moreover, the negative association between social group membership and cluster farming

**Table 6** ESR, binary probit and IPWRA models results on determinants of teff cluster farming participation in Ethiopia

| Variables | ESR | Binary probit | IPWRA |
|---|---|---|---|
| Sex of respondents | −0.023 (0.654) | −0.006 | −0.134 (0.614) |
| Educational status | 0.779 (0.219) *** | 0.272*** | 1.400 (0.447) *** |
| Age of respondents | −0.020 (0.011) * | −0.008* | −0.038 (0.019) * |
| Household size | −0.041 (0.049) | −0.013 | −0.060 (0.078) |
| Landholding | −0.007 (0.100) | −0.003 | −0.032 (0.175) |
| Log (on-farm income) | 0.498 (0.159) *** | 0.173*** | 0.882 (0.275) *** |
| Off-farm income participation | 0.516 (0.242) ** | 0.172** | 0.883 (0.431) ** |
| Neighbor participation in cluster farming | −0.319 (0.269) | −0.143 | −0.627 (0.538) |
| Access to teff storage | 0.343 (0.247) | 0.135 | 0.729 (0.488) |
| Membership in social group | −2.021 (0.222) *** | −0.670*** | −3.576 (0.410) *** |
| Amhara region | 0.257 (0.378) | 0.092 | 0.510 (0.766) |
| Oromia region | 0.215 (0.339) | 0.070 | 0.435 (0.685) |
| SNNP region | 0.332 (0.387) | 0.093 | 0.653 (0.797) |
| Constant term | −5.824 (1.733) *** | | −10.372 (3.051) *** |
| Number of observations | 290 | 290 | 290 |
| Log likelihood test | −34.82 | −103.11 | |
| Chi-square test | 72.35*** | 178.74*** | |

Values in parentheses are standard errors and we reported the marginal effect for the binary probit model

***, ** and * are significance levels at $p < 0.01$, $p < 0.05$ and $p < 0.1$, respectively

**Table 7** Factors affecting teff commercialization of cluster farming participants and non-participants

| Variables | Teff commercialization by participation status | |
|---|---|---|
| | Participant | Non-participant |
| Sex of respondents | 0.0200 (0.083) | 0.0569 (0.117) |
| Educational status | −0.0322 (0.036) | −0.0560 (0.042) |
| Age of respondents | 0.0009 (0.002) | 0.0003 (0.002) |
| Household size | 0.0084 (0.007) | 0.0180 (0.010) * |
| Landholding | 0.0429 (0.014) *** | 0.0173 (0.019) |
| Log (On-farm income) | −0.0404 (0.029) | 0.0564 (0.029) * |
| Off-farm income participation | 0.0876 (0.037) ** | 0.0865 (0.048) * |
| Neighbor participation in cluster farming | −0.0308 (0.038) | 0.1230 (0.053) ** |
| Access to teff storage | 0.0521 (0.042) | 0.0039 (0.050) |
| Amhara region | 0.3140 (0.066) *** | 0.5240 (0.074) *** |
| Oromia region | 0.1950 (0.063) *** | 0.3630 (0.067) *** |
| SNNP region | 0.1650 (0.067) ** | 0.2500 (0.076) *** |
| Constant term | 0.5410 (0.292) * | −0.6840 (0.336) ** |
| Independence of equations test using log-likelihood ratio test = 4.06** | | |

***, ** and * are significance levels at $p < 0.01$, $p < 0.05$ and $p < 0.1$, respectively

participation requires further investigation to identify additional reasons that confirm their inverse relationship.

### Factors affecting teff commercialization of cluster farming participants and non-participants

As depicted in Table 7, different factors affect the teff commercialization level of cluster farming participants and non-participants. For instance, household size positively associated with the commercialization level of cluster farming participants at $p < 0.1$. Teff production consumes more labor than other crops. Hence, having a large household size effectively solves the labor-intensive issues associated with teff production. This will enhance farmers' production potential and their participation in the output market, resulting in a higher commercialization level. This finding is elaborated by Fekadu et al.

(2021), who states that household size increases wheat commercialization by 11%. Similarly, landholding positively correlated with commercialization level of cluster farming participants. Consistent with our finding, the studies undertaken by Ayele et al. (2021), Dureti et al. (2023) and Tufa et al. (2014) confirmed that farmers who have a large land size achieve a higher commercialization level than small land size owners.

On-farm income had a positive association with teff commercialization of non-participants. Thus, the rise in on-farm income leads to a higher level of teff commercialization of non-participants because farm households reinvest their on-farm income in production activities. This shows that having higher on-farm income reinforces farmers' financial capacity to purchase improved agricultural inputs and hire agricultural mechanization to enhance their production and productivity, thereby increase their level of commercialization. Moreover, off-farm income participants have a higher likelihood to increase their level of commercialization than non-participants. This result corresponds with the researches carried out in Ethiopia by Abate et al. (2022) and Fekadu et al. (2021) who emphasized that off-farm income participation fosters commercialization of cereal crops because off-farm income strengthens the agricultural input purchasing capacity of farmers, leading to crop production and market supply increment.

The respondent's neighbor's participation in cluster farming was positively associated with teff commercialization of cluster farming non-participants. Observing the daily activities of their neighbors who have joined cluster farming will encourage non-participants to join cluster farming in future farming practices. This in turn will strengthen their participation in the output market and consequently increase teff commercialization level. Likewise, Amhara, Oromia and SNNP regions positively and significantly related with teff commercialization level compared to Tigray region. This is because the three cluster farming priority regions are potential teff producing and supplying regions at the national level. According to the CSA (2021) report, a total of 26.90, 20.96, 3.74 and 0.38 million quintals of teff were produced in Oromia, Amhara, SNNP and Tigray regions respectively. As discussed by Tadele and Hibistu (2022), Amhara and Oromia regions of Ethiopia cover about 87.8% and 85.5% of teff production and cultivated area, respectively. The authors added that SNNP is the third potential teff producer region. According to Getahun and Milkias (2021), about 45%, 29%, 14% and 13% of smallholder farmers in Oromia, Amhara, SNNP and Tigray regions participated in the cluster farming practice. This suggests that the model result is congruent with the observed differences between regions in the actual situation.

**Table 8** The endogenous switching regression model average treatment effect result

| Cluster farming participation status | Decision stage | | Average treatment effect |
|---|---|---|---|
| | To participate | Not to participate | |
| Participant | 0.57 | 0.43 | 0.14*** |
| Non-participant | 0.36 | 0.44 | −0.07*** |

*** represents significance level at $p < 0.01$

**Table 9** Average treatment effect results of inverse probability weighted regression adjustment model

| Model | Cluster farming participation status | | Average treatment effect |
|---|---|---|---|
| | Participant | Non-participant | |
| IPWRA | 0.57 | 0.51 | 0.06*** |

*** represents significance level at $p < 0.01$

### Impact of cluster farming on teff commercialization

As the ESR result revealed, teff commercialization level of participants (0.57) was higher than its counterfactual (0.43) i.e., assume that participants would not have participated (Table 8). This implies that the commercialization level of participants exceeds their counterfactual by 24.6%. Additionally, the IPWRA model result showed that cluster farming participants commercialized teff by 10.5% more than non-participants (Table 9). Therefore, the ESR result was higher than the IPWRA model. In both models we found a statistically significant average treatment effect result at a significant level of $p < 0.01$. Hence, the impact of cluster farming on teff commercialization was positive and statistically significant. This highlights that cluster farming is a promising marketing initiative for farmers because it improves farmers' domestic market supply, access to transport, market price of their products, market information access and market linkage with potential buyers (Montiflor et al. 2009; Washim et al. 2015). Likewise, Abate (2021) elaborated that cluster farming positively influenced maize commercialization level of smallholder farmers.

Whereas teff commercialization of non-participants (0.44) was higher than the counterfactual (0.36) i.e., suppose non-participants would have participated in cluster farming. This implies that the commercialization of teff would have decreased by 22.2% if the non-participants had participated in cluster farming. This means that cluster farming non-participant have less teff market participation potential than participants. This is because cluster farming prioritizes potential production areas. Thus, less potential areas mainly produce for self-consumption rather than for market. Besides, extension services, technology adoption, market access and other intervention practices specifically prioritize cluster participants over non-participants (Abate 2021; Endaznow 2020; Joffre et al. 2020; Montiflor 2008). As a result, cluster farming non-participants have less income and profit than participants (Satyarini and Pangarso 2021). The possible reason is justified by Kassie et al. (2009), who stated that users and non-users of improved farming practices are systematically different because the selection process is not random. This shows that the model result is consistent with the cluster farming practice context in Ethiopia and the findings of previous studies.

## Conclusion

This study examined the impact of cluster farming on teff commercialization in Ethiopia. The data collected by ATI was used to address the objectives of this study. Then, the data were analyzed using descriptive and inferential statistics, commercialization index, and ESR model. The result revealed that the mean teff commercialization of cluster farming participants (0.57) was more than non-participants (0.44). The mean commercialization difference between participants and non-participants was significant at $p < 0.01$. Besides, the regional level disaggregated result confirms that cluster farming participants had a higher mean teff commercialization than non-participant in all the cluster farming priority regions. We also found a statistically significant mean difference in teff commercialization within the cluster farming priority regions at $p < 0.01$. The ESR result also revealed that cluster farming had positive impact on teff commercialization at $p < 0.01$. Consequently, the t-test, f-test, and ESR results entails that cluster farming enhances smallholder farmer's participation in the market-oriented production system because cluster farming participants sold the majority of their teff production in all the cluster farming priority regions. Conversely, non-participants used the majority of their teff production for consumption and seed. This implies that the promotion of cluster farming facilitates teff commercialization in Ethiopia. The findings of this study were derived from a cross-sectional data collected from 290 sample respondents. The findings could not provide evidence on the impact of cluster farming on teff commercialization over time. Therefore, we recommend further studies using panel data collected from large samples to provide a longitudinal perspective on the impact of cluster farming on teff commercialization over time. Besides, commercialization alone may not sustain the promotion of cluster farming. Therefore, the profitability of cluster farming participants is also essential to decide whether cluster farming practices should be promoted or not. Thus, we suggest that the profitability of teff cluster farming should be studied before embarking on widespread promotion. The findings of these studies can offer comprehensive insights and concrete information that can inform policymakers to support and promote teff cluster farming in Ethiopia.

### Abbreviations

| | |
|---|---|
| ATA | Agricultural Transformation Agency |
| ATI | Agricultural Transformation Institute |
| ATT | Average Treatment Effects of the Treated |
| ATU | Average Treatment Effects of Untreated |
| CSA | Central Statistical Agency |
| ESR | Endogenous Switching Regression |
| FAO | Food and Agricultural Organization |
| HCI | Household Commercialization Index |
| IPWRA | Inverse Probability Weighted Regression Adjustment |
| SNNP | Southern Nations, Nationalities and People's |

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### Author contributions

The authors' contributions are summarized as follows: BE designed the study topic and objectives by reviewing the current literature. Finally, he performed data analysis, interpreted the results, prepared the draft manuscript and revised it based on the comments of AE and KY. AE and KY approved the topic and objectives. They also reviewed, edited and commented on the draft manuscript. Then, AE undertook plagiarism check using iThenticate software before submission to the journal of CABI Agriculture and Bioscience.

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### Availability of data and materials

The data used in our study require permission from the Agricultural Transformation Institute of Ethiopia.

## Declarations

### Ethics approval and consent to participate

No human or animal tissues were used in this study. Procedurally, the similarity index was measured using iThenticate score before journal selection. Then, the plagiarism result was evaluated and confirmed by the United Graduate School of Agricultural Sciences, Tottori University, Japan before submission to the journal of CABI Agriculture and Bioscience. Therefore, the manuscript was seriously evaluated to meet ethical standards before submission.

### Consent for publication

Not applicable.

### Competing interests

The authors declare that they have no competing interests.

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