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Impact of Malt-Barley Commercialization Clusters on Productivity at Household Level: The Case of Selected Districts of Oromia Region, Ethiopia

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Abstract

The Ethiopian government has been implementing a clustering program in smallholder agriculture to transform the sector from subsistence to commercial level via increased quantity and quality of products and thereby income of farmers. Nonetheless, such a program can solicit more resources and best be scaled if its benefits can be well known and documented. To this end, this study aims to evaluate the influence of commercialization clusters on the productivity of malt barley at the household level in the Arsi and West Arsi zones of the Oromia region. A multistage stratified random sampling technique was applied for selecting samples. The sample for this analysis includes 360 households for 180 each member and non-members. Descriptive statistics and Inverse probability weighted regression adjustment were applied to analyze the data. Accordingly, there was a significant difference between members and non-members of the cluster program in age and access to the market. More than a half hectare of land per household is covered with malt barley annually with an average of 24 quintals per hectare. The yield difference was significant between members and non-members on the Nearest-neighbour matching result. Expanding malt barley cluster farming on a larger scale can help the nation in general.

Keywords: Barley, Cluster, inverse probability weighted regression

Introduction

Smallholder farmers who spread over many parts of the world strongly relied on agriculture as the main source of food, income, and employment. Against this background, agricultural development has been acknowledged as one of the main pathways for poverty alleviation (World Bank, 2015). Ethiopia has a total land area of 1.14 million square kilometres of which 45 and 3 % of it is arable and irrigated land respectively. The population density in 2020/21 was 95.8 person per square kilometres (NBE,2021). The Ethiopian economy continued to register growth in 2020/21 amid the instability in the northern part of the country and the impact of the COVID-19 pandemic. During the review fiscal year, real GDP had a 2,114.2 billion Birr volume and showed a 6.3 percent growth, slightly higher than the 6.1 percent growth last year. The growth of real GDP in 2020/21 was attributed to the growth of industry 7.3%, services 6.3%, and agriculture 5.5% . Nominal GDP per capita stood at USD 1,092, depicting a 1.1 percent marginal improvement relative to the previous year (NBE, 2021). In a similar mid-year, Ethiopia's population with more than 80 percent living in rural areas reached nearly 101.9 million. From 2011 to 2016, poverty dropped by 20 percent in Ethiopia. However, poverty in rural areas increased during the same time frame (World Bank, 2015).

Agro-clusters relate to the indigenous specialisation and attention of an agricultural commodity. They encompass tilling conditioning, recycling units, and trades (Dadan *et al*, 2015). Indeed, as Barrett, (2008) and Barkley and Henry (1997) depicted, agro-clusters may play an important role in reducing poverty rates by offering profitable growth at the micro-level by raising productivity. The clusters may offer positive externalities and invention (Ferragina and Mazzotta, 2014). Secondly, agricultural productivity growth may be associated with advanced profitable performance and a lower poverty rate (De Janvry and Sadoulet, 2010). Barley is the hardest of all cereal grains. It's one of the first cultivated grains in history and it remains one of the most extensively consumed grains, worldwide. Its civilization extends further north than any other crop and at the same time, it can be cultivated in sub-tropical countries (Hailemiceal *et al*, 2011). Barley has a short growing season and is also fairly failure and saltiness tolerant. Worldwide, barley is ranked fourth among grains in volume produced behind sludge, rice, and wheat (FAO,2020).

Barely was officially introduced as a food crop by Ethiopia which the country became a center of origin and diversity for this crop, and landraces have been cultivated by farmers for further than 5000 years. The country is also the top barley patron in Sub-Saharan Africa, with 3.7 million farmers in 2019 (CSA, 2019). Barley kinds are generally classified in two orders: food barley and malt barley. Ethiopian product of malt barley is inadequate to meet domestic demand, and the country accounts for nearly two- thirds of its consumption (Kosmowski *et al*, 2020). In order to increase product and at least meet the domestic demand, a commercialization cluster program has been enforced in malt barley products. In order to ensure sustainable relinquishment and promote upscaling, its benefit and the associated good practices should well be known. Given the indigenous capabilities of Oromia malt barley product, marketing and consumption, there's meagre information about the profitable impact of malt barley slightly commercialization clusters. To this end, this study has the ideal of assessing the impact of commercialization clusters on the productivity of malt barley slightly at the ménage position in the Arsi and west Arsi zones of the Oromia region.

Material and Methods

Description of the Research Area

This study is undertaken in the Arsi and West Arsi zones in the Oromia region of Ethiopia. The zones produce different types of agricultural products including cereals, pulses, vegetables and fruits. Malt barley is the dominant cereal crop based on both the size of land allocated to it and the number of households producing in the respective zones (Zones offices of MOA). From the selected zones, two districts namely Kofele and Digelu Tijo from West Arsi zone and Tiyo district from Arsi Zone were selected based on their extent of malt barley production. The altitude of Kofele woreda ranges from 2000 to 3050 meters above sea level. Digelu Tijo wereda has an estimated area of 889.22 square kilometres, it has a latitude and longitude of 7°45′N 39°15′E with average elevation of 2,713 meters. Tiyo Wereda is located 175 km Southeast Addis Ababa at 7°56′N 856E and 39°08′N 260E, 2436 masl and it is one of the Twenty Weredas found in Arsi Zone of Oromia Regional State situated in the North Western part of the Zone.

Type and Method of Data Collection

The survey was administered on sample households that are drawn using a multistage stratified random sampling technique. Structured questionnaires were prepared and administered by pre-testing it for inclusion of any necessary details. Our target population is malt barley producers in West Arsi and Arsi zones who have at least one-year experience of growing malt barley as a means of inclusion into the study. In the first stage, three districts (two from West Arsi and one from Arsi) zones were chosen based on their malt barley production potential and participation in malt barley markets. In the second stage, three farmers' associations (kebeles) per district were randomly selected. In the third stage, malt barley producing households were stratified in each kebele as participants and non-participants in malt barley commercialization cluster farming. From each district, three kebeles were selected namely Gurimich, Buchi and Afamo from Kofele district, Digelu Bora, Sagure Molea and Shaldo Mankula from Digelu Tijo district and Haro Bilalo, Dosha and Ankaka Koncha from Tiyo district. A total sample of 360 of which 180 members and 180 non-members of malt barley commercialization cluster farming. Finally, representative sample households were selected using probability proportional to size (PPS). To determine the desired sample size, a formula developed by Krejcie (1970) was applied. Hence, using 95% level of confidence and chi-square value for one degree of freedom, and proportion of population assumed to be 0.5 with degree of accuracy of 0.05, the sample size was determined based on the formula given by

$$n = \frac{X^2NP(1-p)}{d^2(N-1)+X^2P(1-p)} = \frac{(3.841)^2X30{,}492X0.5(1-0.5)}{(0.05)^2(30{,}492-1)+(3.841)^20.5(1-0.5)} = 360$$
(1)

Where:
n = required sample size
X^2X^2 = tabulated value of chi-square for 1 degree of freedom at 5% significance level (3.841)
N = the population size which is the size of Malt barley farm households
P =proportion of population assumed to be 0.5 since this would provide maximum sample size
d = the degree of accuracy expressed as proportion (0.05) i.e. standard error

Identification strategy

The major challenge in evaluating the impact of a given intervention is the unavailability of baseline data. Finding a valid counterfactual group is key to identify the impacts but in the absence of baseline data, we could not rely only on quantitative approaches. Thus, we adopted a mixed-method approach from the design stage of the impact evaluation. The counterfactual selection process has proceeded as follows.

First, we obtained the full list of farmers in malt barley commercialization clusters and non-members as well. The lists of farmers served as a population for selecting sample size determination. Nearest neighbourhood matching was run for each district to match the members and non-members of the cluster farming. In each district, the matching variables included binary indicators of sex of household, availability of access to information, presence of training, credit constraints, and oxen for cultivation rent for tractor, rent for combined harvester, extension worker contacts, and access to improved malt barley seed.

Non-members of malt barley commercialization cluster farming that did not fall within the common support with the data collecting peasant association were dropped. From the list of farmers found from the administrative office of the selected peasant association, participants of commercial cluster farming were prepared with up to two replacements (second and third best match). Both lists of members and non-members of the cluster were validated by development agents based at the peasant association. The lists were ranked best, second and third matched. Both quantitative and qualitative matching methods were applied to list members and non-members of cluster farming. The second step was the selection of counterfactual households. Even though members and non-members were curiously similar, we had to make sure the counterfactual households were similar from members of cluster farming households.

Inverse probability weighted regression adjustment (IPWRA)

The fundamental concept of using the propensity score matching system is erected on a strong supposition that observable characteristics determine the selection of treatment and control groups. Thus, matching estimators are frequently disposed to selection bias. This allows us to control for selection bias at both the treatment and outgrowth stages. Therefore, the IPWRA estimator has the double-robust property, which means that only one of the two models is rightly specified to constantly estimate the impact (StataCorp, 2017). The Inverse probability weighted regression adjustment estimators use a model to prognosticate treatment status, and they use another model to prognosticate issues. Because IPWRA estimators have the double-robust property, only one of the two models must be rightly specified for the IPWRA estimator to be harmonious.

This study also used the IPWRA approach to identify the impacts of cluster farming on malt barley productivity. In order to achieve this ideal, the study applies the ‘ teffects IPWRA command in STATA 15 and estimates the model. The average Treatment Effect for Treated (ATET) is estimated to probe the impacts of cluster husbandry practice. The variables like sex, education, age, family size, ranch experience, training, access to bettered seed, access to fertiliser, the distance of the main road to a ménage head occupant, the distance of the extension office from the homestead, access to credit malt barley slightly yield were included.

We use both parametric and non-parametric styles to estimate the malt barley slightly commercialization cluster average treatment effect (ATE) and treatment effects on the treated (ATT). Ordinary least squares (OLS) is used to estimate ATE on income, prices, trade volumes, and other livelihood issues. Inverse probability weighted regression adjustment (IPWRA) is used to estimate ATT, non-parametrically. In the absence of baseline data, these estimators control for selection on observable attributes only. Selection bias from unobservable attributes isn't controlled for, but we perform several robustness checks. Equation 1 shows the estimating equation for the OLS estimator.

$Y_i = \propto + \beta T_i + \gamma X_i + \varepsilon_i Y_i = \propto + \beta T_i + \gamma X_i + \varepsilon_i$-------------------------------------(2)

Y_i is an outcome interest, T_i is the double index for malt barley slightly commercialization cluster husbandry, X_i is the vector of observable characteristics of the household i, and ε_i is the error term. Standard errors are clustered at the household level because utmost product opinions and practices are made by the individual household. The coefficient β is the estimate of the malt barley commercialization cluster husbandry impacts on outcome Y.

The IPWRA estimator combines the inverse probability weighted (IPW) and the retrogression adaptation (RA) estimators. The regression adjustment method adds one further term in the OLS equation (1) – the commerce between being a member of cluster framing indicator and mean corrected control covariates ($\boldsymbol{X}_i - \bar{\boldsymbol{X}}$). It has been used preliminarily to estimate the impacts of agrarian interventions (FAO, 2020; Montiflor, 2008). Specifically, the retrogression specification is as follows

$Y_i = \propto + \beta T_i + \gamma X_i + \delta(X_i - \bar{X})T_i + \varepsilon_i Y_i = \propto + \beta T_i + \gamma X_i + \delta(X_i - \bar{X})T_i + \varepsilon_i$-(3)

In Equation 2, $\bar{\boldsymbol{X}}$ is the vector of the average of the observable characteristics of household i, and β is the ATE estimate, which is mathematically represented as

$$\beta_{ate} RA = \frac{1}{N}\sum_{i=1}^{N}[E(Y_i|X_i, T_i = 1) - E(Y_i|X_i, T_i = 0)]$$

$\beta_{ate} RA = \frac{1}{N}\sum_{i=1}^{N}[E(Y_i|X_i, T_i = 1) - E(Y_i|X_i, T_i = 0)]$-----------------------------(4)

Replacing $\bar{\boldsymbol{X}}$ with $\bar{\boldsymbol{X}}_i$ in equation 3 (where $\bar{\boldsymbol{X}}\boldsymbol{i}$ is the average over treatment households only) yields the ATT estimate.

The inverse probability weighted (IPW) estimator gets rid of the confounding factors by creating a pseudo-population. It uses the antipode of the estimated propensity score as weight (Wooldridge, 2010). The propensity score can be estimated using probit and also used to cipher the treatment goods as follows

$\beta_{ate,IPW} = \frac{1}{N}\sum_{i=1}^{N}\frac{[T_i - \rho(X_i)Y_i]}{P(X_i)[1-\rho(X_i)]}\beta_{ate,IPW} = \frac{1}{N}\sum_{i=1}^{N}\frac{[T_i - \rho(X_i)Y_i]}{P(X_i)[1-\rho(X_i)]}$ ---------------------- (5)

The IPWRA models the likelihood of malt barley commercialization cluster participation and estimates the cluster impacts contingent on the liability (Rola *et al*, 2013; Rosenbaum *et at*, 1983). Each observation in the dataset is assigned weights according to the following matrix

ww(t,x)=t + (1-t)$\frac{p(x)}{1-P(X_i)}\frac{p(x)}{1-P(X_i)}$--- (6)

Where ω(t,x) is the weight applied, t represents $T_i = 1T_i = 1$, $P(X)$ is the estimated propensity score and X is a vector of covariates.

Our preferred method for this analysis is the inverse probability-weighted regression adjustment (IPWRA) method for its doubly robust properties. Both the matching and regression adjustment methods may have issues of selection bias because both of these methods can account for observable characteristics only.
IPWRA estimators use probability weights to obtain outcome-regression parameters that account for the missing-data problem arising from the fact that each subject is observed in only one of the implicit issues. The adjusted outcome-regression parameters are used to compute averages of treatment-level predicted

outcomes. The contrasts of these averages provide estimates of the treatment effects. Because IPWRA estimators have the double-robust property, only one of the two models must be correctly specified for the IPWRA estimator to be harmonious (Wooldridge, 2010)..

IPWRA estimators use a three-step approach to estimate treatment effects:

1. We estimate the parameters of the treatment model and compute inverse-probability weights.
2. Using the estimated inverse-probability weights, we fit weighted regression models of the outcome for each treatment level and obtain the treatment-specific predicted outcomes for each subject.
3. We compute the means of the treatment-specific predicted outcomes. The contrasts of these averages give the estimates of the ATEs. By confining the calculations of the means to the subset of treated subjects, we can gain the ATETs.

Results and Discussions

Descriptive Statistics

The results of descriptive statistics play a significant role to verify the econometrics results. It helps to provide information regarding the sample respondents and variables used in the econometrics model. Accordingly, Tables 1 and 2 present the descriptive statistics of variables used for this study. The mean age of the sample respondents categorised in combined, members and non-members of malt barely commercialization clusters is 40.7 years having no significant difference between members and non-members of malt barley cluster farming. The family size and farm experience were 6 persons and 12 years, respectively of which both have no significant difference between members and non-members. Members have better market access with 2.75kms than non-members (3.05km) with a significant difference at 5%.

The average area covered by malt barely is 0.65 hectares with an average yield of 24 quintals per hectare. There was a significant difference in malt barely seed rate amount between members and non-members of cluster farming. However, this rate difference was not significantly reflected on the final harvest per hectare (Table 1).

Table 1. Summary statistics of the continuous variables used in the analysis

Variables	Combined (360)		Members of MB ACC (180)		Non-Members of MB ACC (180)		t-test
	Mean.	Std.Dev	Mean	Std.Dev.	Mean.	Std.Dev	
Age-HH	42.6	12.15	42.77	12.20	38.72	11.04	0.334
Family size	6.41	3.42	6.42	3.43	6.37	3.40	-0.619
MB experience(yrs)	12.72	10.15	12.82	10.23	11.66	9.31	-0.492
Dist. to market (Km)	2.78	2.38	2.75	2.35	3.05	2.61	-2.167
Dist. to FTC (minute)	26.6	19.55	26.84	19.73	24.23	17.81	0.442
MB- yield (Qt/ha)	23.47	13.09	25.65	14.31	23.31	13.00	-0.430
MB-area(ha)	0.64.	0.43	0.65	0.43	0.64	0.43	1.603
MB seed rate (Kg/ha)	128	37	137.60	39.78	127.49	36.85	5.986

Source- Authors' calculation using the survey data, 2021, MB- Malt Barley

The household sex composition, access to market information, training opportunity, the existence of constraints on credit, availability of oxen, rent of tractor for ploughing, rent of combined harvester, extension worker contact and access to improved malt barley seed were selected as categorical variables. Accordingly, there is a significant difference between members and nonmembers of malt barley cluster farming on availability of oxen, rent tractor for ploughing, combined harvester and extension worker contact (Table 2).

Table 2. Summary statistics of the categorical variables used in the analysis

Variables	Combined (360)		Members of MB ACC (180)		Non-Members of MB ACC (180)		X^2-test
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev	
Sex-HH	0.86	.35	0.88	0.36	0.78	0.32	1.591
Acc. to Mart info. (Y/N)	0.97	0.16	0.97	0.16	0.97	0.16	1.692
Training (Y/N)	0.71	0.29	0.76	0.31	0.69	0.28	1.145
Credit constraint (Y/N)	0.42	0.61	0.42	0.61	0.42	0.61	3.045
Oxen for cultivation (Y/N)	0.76	0.24	0.88	0.19	0.64	0.42	12.713
Rent tractor for ploughing (Y/N)	0.61	0.45	0.78	0.27	0.44	0.63	7.977
Rent combined harvester (Y/N)	0.79	0.24	0.92	O,09	0,66	0.46	13.203
Extension worker contact (Y/N)	0.73	0.28	0.89	0,19	0.57	0.48	11.515
Access for improved Malt barley seed (Y/N)	0.59	0.44	0.67	0.35	0.51	0,48	1.726

Source: Authors' calculation using the survey data. 2021, Y/N- Yes/No

Econometrics Results

Impact of malt barley commercialization cluster on productivity

De Janvry and Sadoulet (2010) and Louhichi *et al* (2019) highlighted for ensuring the balancing condition is a decisive issue in PSM as it reduces the influence of confounding variables. Hence, a covariate balancing test was done as presented in

Table 3. The result shows that the pseudo-R^2 was also reduced significantly from 11.4% before matching to a range of 0.4–0.8% after matching and was equitably low, indicating that after matching there were no systematic differences in the distribution of covariates between the two studied groups (members and non-members of malt barely commercialization clusters). The total bias was also reduced significantly via the matching process. Furthermore, all covariates in the probit model depicted a significant difference in the post matching comparison in the P-values of LR tests which was not in the before matching. The standardised mean difference for overall covariates used in the estimation process reduced from 31.7% before matching to a range of 3.2–5.4% after matching. Hence, specification of the propensity score estimation process is successful in balancing the distribution of covariates between members and non-members.

Table 3. Matching quality indicators before and after matching

Matching algorithm	Pseudo- R^2		LR chi^2		P> chi^2		Mean standardized bias		Total % bias reduction
	Before matching	After matching	Before matching	After matching	Before matching	After matching	Before matching	After matching	
Nearest neighbor	0.114	0.004	59.94	2.96	0.00	0.988	31.7	3.9	97.6
Radius matching	0.114	0.008	59.94	3.76	0.00	0.866	31.7	5.4	99.4
Kernel matching	0.114	0.005	59.94	3.41	0.00	0.955	31.7	3.2	96.9

Source: Field Survey data calculated by authors, 2021

Result of Average Treatment Effect on Treated (ATETs)

The result of PSM becomes unbiased and consistent when the selection equation is correctly specified. However, according to Wossen *et al* (2017), the result can be biased if there is a misspecification of the propensity score matching model. The IPWRA results in Table 4 show that the causal effects of being the member of malt barley commercialization cluster on household net income is nearly 36% more than non-members of cluster farming with a significant difference at 1% level of significance. The involvement of members and non-members of MB commercialization cluster farming on purchase of agricultural inputs like fertilizer and chemicals was assessed and there was a significant difference depicted as cost. Members are very much aware about how to compensate for the overall production cost of malt barley with the revenue they get from the sale of their harvest. Accordingly, the result depicted in table 4, members incurred 11% more than non-members. However, this difference leads members to harvest 9% yield more than non-members and earn more. There was a significant difference on prices of MB between members and non-members of cluster farming; This could be because of early access to the market, proper quality standard setting mechanisms among members, high bargaining power of big volume supply and quality packaging services. This finding, supported by Bernard *et al* (2008) , shows that being a member of an agricultural cooperative can give its members a better price and relatively pleasant way of payment scheme. Similarly, our result of a progressive association between cluster farming and getting better price for their harvest is also in line with Barham & Chitemi (2009) for Tanzania, their findings suggest that cooperatives improve market performance.

Farmers in the study area are also involved in producing other crops like wheat and vegetable crops. Accordingly, there was a significant difference between members and non-members of the MB commercialization cluster at 10% level of significance. This finding is similar with the findings of Yuying *et al* (2019) who reported a positive impact of agricultural cooperatives in searching for a better market for members resulting in a higher income in China.

Table 4. Average treatment effects using IPWRA

Performance indicators	Mean Outcomes		Differences (ATT)	% Change
	Members of MB Cluster farming	Non-Members of MB Cluster farming		
Yield (Qt/ha)	25.65	23.31	11.84 (3.47)***	9.12
Cost (ETB /ha)	5726	5095	763 (68)***	11.02
Price (ETB/ Qt)	3550	2950	730 (80)***	16.91
Share sold (%)	67	59	0.102(0.03)***	11.94
Net Income (ETB)	55,282.53	35476.05	42,434(11573)***	35.82
Income from other crops (ETB)	10201	10050	172 (75.32)*	2.27

Source: Field survey, 2021 standard errors in parenthesis ***P<0.01, **P<0.05, *<0, 10, ETB-Ethiopian Birr, MB- Malt barely

Inverse Probability Weighted Regression Adjustment (IPWRA)

To check the robustness of the study results from PSM findings, we employed IPWRA to address misspecification bias. Table 5 below reports the mean differences of treatment effect estimates for cluster farming participation on malt barley productivity and commercialization using PSM and IPWRA estimation techniques. The result shows the yield of malt barley cluster farming practice and non–cluster farming practice is 26 qt/ha and 23 qt/ha, respectively. Participation in cluster farming increases malt barley yield by about 3 qt/ha (13%) change using the IPWRA specifications. It can be seen from the result that the impact of cluster farming practice participation is robust for both estimation strategies, showing the important role of cluster farming practice on better malt barley productivity. This finding is supported by the finding by Rola-Rubzen *et al* (2013) who reported that farmers could take some advantage of being a member of agricultural commercialization clusters mainly for agricultural input distribution, information exchange on reducing transaction costs, better agricultural practice implementation, and boosting bargaining power both for input purchase as well as output selling.

Table 5. Average treatment effects on treated (ATT) using inverse probability weighted regression adjustment (IPWRA) model

Outcome indicators	Mean outcomes		ATT difference	Percent change
	CLFP	NCFP	CLFP vs NCFP	
Malt Barley yield(qt/ha)	25.66	23.31	2.93(0.74) ***	9.15

Robust standard errors are reported in parentheses, *** represent statistical significance at the 1% levels. CLFP-Cluster farming practice, NCFP-Non-cluster farming practice.
Source – Own survey result, 2021

Conclusion and Policy implication

In this study, we examine the impact of malt barley cluster farming on household malt barley productivity in Arsi and West Arsi zones of Oromia Region, Ethiopia. We employ Inverse probability weighted regression adjustment models for assessing these relationships. We use household survey data from two zones of the region where malt barley is one of the dominant crops in terms of area coverage. According to our results, the following main conclusions are drawn. The initial conclusion about the impact of being a member of malt barley cluster farming on household productivity verified that farmers who are in cluster farming had an opportunity to get more yield than non-members.
The IPWRA results indicate that being a member of the MB commercialization cluster in sampled areas has a 36% net income difference than non-members of cluster farming. The membership of the malt barley commercialization cluster creates an opportunity to sell more shares of their harvest than non-members. The annual area coverage on malt barley is more than a half hectare per household with a mean yield of 24 quintals per hectare. The Nearest-neighbor matching result indicated a significant yield difference between members and non-members of small malt barley commercialization clusters. We found that malt barley cluster farming resulted in intensification of malt barley production, increased commercialization of malt barley, better quality yield, higher farm gate prices, increased net malt barley income. Our estimated results are robust, consistent across different matching methods.

The result also suggests that strengthening farmers' organizations on cluster farming are critical for potentially enhancing, not only access to and use of agro-inputs, but also facilitating access to Malt barley markets through boosting quality, arranging easy ways for information and knowledge as well as creating flexible platform for involvement of policymakers. The result also indicates that supporting malt barley cluster farming in the malt barley chains is an effective way to contribute to reaching the government aim of expansion and intensification of malt barley production and quality upgrading. Public support on capacity building of farmers who are involved in cluster farming also helps smallholder linkages to modern chains and the smooth functioning of cluster arrangement. The findings of this study stress the need for relevant intervention policies particularly on expanding cluster farming into wider areas of the region in particular and nationwide in general.

Availability of data and materials

Data used for the analyses in this article are available from the corresponding author upon request.

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Contributions

The corresponding author contributed to survey design, data collection, cleaned the data, analyzed the data, and wrote the first draft of the manuscript. The other authors contributed to reading, editing, and structuring the manuscript. All authors read and approved the final version of the manuscript.

Declaration of competing interest

The authors declare that they have no competing interests.

Data availability

Data will be made available on request.

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Notes

a) Kebele is the smallest administrative hierarchy in Ethiopia.

b) Every kebele administration has a full list of households living in the area. We used this list as a sample frame. When the randomly selected farmer does not produce malt barely s/he was replaced by the farmer next to him/her on the list.

c) List and definition of variables used for this study are presented in Table:A_1

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Appendix

\Table A_1. List and definition of variables used

Variable	Unit	Definition
Improved MB seed	Dummy	1 if the farmers utilized improved MB varieties; 0 otherwise.
Age_HH	Dummy	Years Number of years the household head live
Sex_HH	Dummy	1 if the household is male; 0 otherwise
Education HH	Dummy	1 if the household head is literate; 0 otherwise.
Malt Barely Experience	Years	Number of years the household head cultivated malt barely
Membership of MB CC	Dummy	1 if the household is member of MB Commercialization custers ; 0 otherwise
Extension contact	Days	Number of contacts with the extension agent per year
Access to Market info	Dummy	1 if the household has access to market information; 0 otherwise
Training	Dummy	1 if the household gets training regarding maize production; 0 otherwise
Social Responsibility	Dummy	1 if the household social responsibilities; 0 otherwise
Credit constraint	Dummy	1 if the household faces credit constraints; 0 otherwise
Distance to market	Minute	Walking distance between the house of the respondent and the nearest market
Distance to FTC	Minute	Walking distance between the house of the respondent and farmers training center
Family size	Number	Number of family members
Malt barely yield	Kg	physical amount of malt barely produced
Malt barely _area	Hectare	Size of land that allocated to Malt barely production
Malt barely _ Fertilizer	Kg	Amount of fertilizer used for malt barely production
Malt barely _ seed	Kg	the quantity of Malt barely that used
Malt barely _ labour	Man-equivalent	both family and hired labor used for different agronomic practices of malt barely production