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ORIGINAL ARTICLE

The new normal? Cluster farming and smallholder commercialization in Ethiopia

Guyo Godana Dureti[1,2,3] | **Martin Paul Jr. Tabe-Ojong**[4] | **Enoch Owusu-Sekyere**[2,5,6]

[1]Ethiopian Agricultural Transformation Agency, Addis Ababa, Ethiopia

[2]Department of Economics, Swedish University of Agricultural Sciences, Uppsala, Sweden

[3]Institute for Food and Resource Economics, Rheinische Friedrich-Wilhelms-Universität Bonn, Bonn, Germany

[4]International Food Policy Research Institute (IFPRI), Cairo, Egypt

[5]Department of Agricultural Economics, Extension & Rural Development, University of Pretoria, South Africa

[6]Department of Agricultural Economics, University of the Free State, Bloemfontein, South Africa

Correspondence
Guyo Godana Dureti, Land Economics Group, Rheinische Friedrich-Wilhelms-Universität Bonn, Bonn, Germany.
Email: Guyogodana544@gmail.com

Abstract

Cluster farming is increasingly recognized as a viable means of improving smallholder economic integration and commercialization in many developing countries. However, little is known about its impact on smallholder welfare and livelihoods. We examine the relationship between cluster farming and smallholder commercialization using a large-scale survey of 3969 farm households in Ethiopia cultivating high-acreage crops such as teff, wheat, maize, barley, and sesame. Using switching regressions and instrumental variable estimators, we show that cluster farming is associated with commercialization measured as commercialization index, market surplus value, and market price. To further deal with endogeneity concerns, we also employ some pseudo-panel models where we observe similar insights. Beyond this, we account for heterogeneities by disaggregating households based on farm scales and crops cultivated. Our findings show that cluster farming is positively associated with commercialization for all farms and crop types despite this disaggregation. However, the related gains are higher among medium and large farms and vary per crop type. These findings imply that cluster farming is crucial in improving smallholder commercialization and may be a critical entry and leveraging point for policy. We thus lend support to initiatives and plans that seek to upscale cluster farming as they can potentially improve smallholder commercialization with ensuing impacts on rural livelihoods and welfare.

KEYWORDS

cluster farming, endogenous switching regression, Ethiopia, market price, market surplus value, smallholder commercialization

JEL CLASSIFICATION

C21, I31, Q12, Q13

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1 | INTRODUCTION

In many developing countries, agriculture remains in the hands of smallholders and has significant potential for long-term growth (Galvez-Nogales, 2010; Abafita et al., 2016; Tafesse et al., 2020). But for agriculture to serve as a sustainable engine of growth, there needs to be a transformation from subsistence farming systems to ones based on commercial-oriented production (Zhou et al., 2013; Woldeyohanes et al., 2017). The transition from subsistence agriculture to commercial-oriented production is an indispensable pathway for poverty reduction, food security enhancement, and the nutritional improvement of farm households (Mamo et al., 2017; Gidelew et al., 2022). Smallholder commercialization is associated with an increase in diversity of marketed commodities on a national scale, an increase in comparative advantage-based specialization on a regional and farm scale, and large-scale production and economies of scale (Barrett, 2008; Jaleta et al., 2009). Furthermore, it is increasingly recognized that the commercialization of small-scale farming output is closely related to higher productivity, greater specialization, and higher income at the micro-level (Barrett, 2008; Bernard et al., 2008). Moreover, at the macro level, commercialization also increases food security and, more generally, improves allocative efficiency (Fafchamps, 2005; Bernard et al., 2008). Therefore, commercialization is critical in the push for smallholder wealth generation, long-term growth, and improved livelihoods.

Recent studies have identified agricultural commercialization as a relevant policy that can significantly improve nutritional status, income, poverty and welfare (Cazzuffi et al., 2020; Haji, 2022; Ogutu & Qaim, 2019; Tabe-Ojong et al., 2022a). Cazzuffi et al. (2020) show that commercialization improves household asset accumulation in Vietnam. In Ethiopia, Haji (2022) finds that commercialization reduces undernutrition among children in the short run. In addition, a study by Ogutu & Qaim (2019) reveals that agricultural commercialization minimizes several dimensions of poverty such as income poverty. Using chickpea production in Ethiopia as a case, Tabe-Ojong et al. (2022a) further show that agricultural commercialization is positively associated with assets, livestock ownership and income. Despite these potential impacts of commercialization, little work has explored key entry and leveraging points for increasing agricultural commercialization (Tabe-Ojong et al., 2022b). Cluster farming offers the promise of being one key policy tool that could be used to boost smallholder commercialization.

Cluster farming offers some pathways to improving farm production and productivity with ensuing impacts on smallholder commercialization (Goetz et al., 2004; Montiflor et al., 2015). It has been highlighted as improving smallholder economic integration and commercialization in many developing countries through its role as a suitable avenue for implementing development projects, disseminating extension services, connecting farmers to input and output markets and providing farmers with access to capacity building and innovations, inter alia (Goetz et al., 2004; Joffre et al., 2019). The concept of cluster farming is defined as a concentration of agricultural activities that generate income and employment opportunities in and around a specific area (Galves-Nogales & Webber, 2017). In cluster farming, a group of smallholders usually pool their resources together for agricultural production, coordinate and market their products jointly, and consequently reduce transaction costs, lower information asymmetries, and improve bargaining power (Fischer & Qaim, 2012; Liverpool-Tasie, 2014). Given this group coordination, cluster farming can serve as an efficient mechanism for extension services and private companies to reach and interact with multiple farmers and share agriculture-related information (Joffre et al., 2019). It could also ease the coordination efforts of governments and development actors in reaching out to farmers, especially for targeted input provision (fertilizers, improved seeds, credit, mechanization, etc.) and support services such as extension, training, and capacity-building initiatives.

In this study, we investigate the relationship between cluster farming and smallholder commercialization in Ethiopia. Ethiopia is an interesting case study because the government has been using cluster farming as a vehicle for poverty reduction and rural development since 2010 (Louhichi et al., 2019). The cluster farming initiative in Ethiopia primarily focuses on facilitating the transition of smallholder farmers from pure subsistence to semi-subsistence/semi-commercial farming (ATA, 2019a). In this cluster approach, smallholder farmers with adjacent land link up in a bid to achieve economies of scale through a greater affordability of modern technology (e.g., sharing the overhead costs of purchasing tractors), stronger bargaining power (e.g., negotiating favorable prices), stronger market linkages to serve large-scale buyers (e.g., contract farming with large processors), and quicker dissemination of best practices and extension services among cluster members (Louhichi et al., 2019; Tabe-Ojong & Dureti, 2023).

We use pooled cross-sectional survey data from 3969 farm households in four major regions of Ethiopia to assess the association of cluster farming with market surplus-value (MSV), commercialization index (CI), and market price (MSP) of smallholder farmers. We estimate endogenous switching regression (ESR) and instrumental variable (IV) models as they account for both observable and unobservable heterogeneities in cross-sectional data settings. To further account for endogeneity concerns and as a form of robustness, we also perform some pseudo panel analysis where we aggregate the household level data to the kebele-level. We then perform fixed effect (FE) and correlated random effect (CRE) estimations. Moving beyond average mean associations, we perform some heterogeneity analysis across a variety of households with different farm size classifications as well as the crops they cultivate in the cluster. Our findings indicate a positive association between cluster farming, MSV, CI, and MSP. The results from the heterogeneity analysis suggest that cluster farming is associated with smallholder commercialization for all farms and crop types, but the associational gains are relatively higher among medium and large farms and exhibits some varying degrees for crops supporting information.

We make several contributions to the body of literature on cluster farming and smallholder commercialization. First, we add to the paucity of empirical evidence on the role of smallholder cluster farming, particularly in developing countries (e.g., Zhang & Hu, 2014; Montiflor et al., 2015; Wardhana et al., 2017, 2019; Tabe-Ojong & Dureti, 2023). Here, we show that improving cluster farming is one of the ways to improve smallholder commercialization. To the best of our knowledge, this is one of the first studies that quantitatively examines the relationship between cluster farming and smallholder commercialization. Montiflor et al. (2015) evaluate the role of cluster farming in improving access to institutional markets and market information and linkages in the Philippines. They show that cluster farming improves access to inputs and increases market surpluses. However, their study only applies a before-and-after comparison of participating households, without rigorously controlling for observable and unobservable heterogeneities that may be in the way of these relationships.

Second, our article attempts to enrich the literature by investigating the relationship between cluster farming and smallholder commercialization using ESR and IV estimators that control for selection and endogeneity issues in cluster farming. Moreover, ESR offers the possibility to estimate actual-counterfactual relationships, which is very relevant for agricultural and development policy (Tabe-Ojong, 2022). It indicates the effect of cluster farming on not only cluster participants but also non-participants, should they participate, which provides policy implications for scaling up the approach in other areas. The third contribution comes from moving beyond average effects to estimate the heterogeneous effect of cluster farming for households at various scales of production. Insights here generate more options for addressing farm households' diverse needs through more inclusive and targeted policy actions. Relatedly, we also consider heterogeneity by crop type. Farmers produce different crops for varying reasons and objectives. While some of the cluster crops such as teff, wheat and maize are staples that are both consumed and sold in markets, others such as malt barley and sesame are more commercial crops. This implies there could be crop-specific differences in some of the outcome variables. Providing these disaggregated analyses is not only indicative of actual realities on the ground but also suggests areas where policy can come in to support farmers at different scales and in various regions.

The final contribution is to the large literature that has shown that commercialization improves smallholders' welfare, food security, nutritional outcomes, and consumption levels (e.g., Carletto et al., 2017; Cazzuffi et al., 2020; Haji, 2022; Ogutu & Qaim, 2019; Tabe-Ojong et al., 2022a). We add to this literature by identifying a key entry point to boost smallholder commercialization. We argue that cluster farming could be a good policy option for facilitating entry into commercialization, particularly among smallholder farmers in developing countries. Moreover, cluster farming in Ethiopia focuses on major staples in the country, which are perceived as inclusive food value chains with the possibility of ensuring food security, nutrition, and long-term poverty reduction.

The rest of the study is organized as follows. Section two briefly discusses the contexts and concepts of producer organizations initiatives and commercialization. Section three outlines the empirical strategy and econometric procedures used to estimate the association between cluster farming and smallholder commercialization. Section four presents the results and discussion. Finally, section five summarizes the main findings and draws policy implications and an outlook for further research.

2 | CONTEXTS AND CONCEPTUALIZATION

2.1 | Literature on producer organization initiatives

To better frame the article within the extant literature and structure our contribution in the face of different producer organization initiatives globally, more specifically in Ethiopia, we highlight the various initiatives that have been rolled out as part of the government's plan to increase welfare and stir rural development. Closely related producer organization concepts, such as cooperatives, associations, agro-clusters, contracts, groups, or other related terms are common in many farming systems (e.g., Bernard et al., 2008; Barham & Chitemi, 2009; Liverpool-Tasie, 2014; Mishra et al., 2018; Dubbert, 2019). These producer organizations could take different forms, such as a bottom-up voluntary based collective action initiative with horizontal or vertical integration or a top-down

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government- or private-led initiative, where each may have different implications for farmers participating in them, at least from a conceptual standpoint. The process of establishing them may also differ regarding whether initiatives are instigated internally by farmers or externally by the government, NGOs, or private entities. Berdegué (2001) and Hellin et al. (2009) highlight that producer organizations established with public support (government or NGOs) often face financial difficulties, which tends to isolate them from the marketing context as they rely more and more on the support provided (e.g., subsidies), whereas for private sector supported producer organizations, the common challenges are equity and sustainability in cases where one party benefits at the expense of the other.

Several empirical studies on producer organizations stress the role of these initiatives in improving market conditions and welfare outcomes in many developing countries. Using the case of government-led farm groups in Tanzania, Barham & Chitemi (2009) show that more mature groups with strong internal institutions, functioning group activities, and a good asset base of natural capital are more likely to improve their market performance. In Kenya, cooperative organizations have been shown to improve income (Fischer & Qaim, 2012), income and asset aspirations (Tabe-Ojong et al., 2020), and women's empowerment (Mwambi et al., 2021). Verhofstadt & Maertens (2015) highlight that cooperatives increase income and reduce poverty in Rwanda, but the effects are higher for larger farms and in remote areas. In China, cooperatives have been shown to improve farm income (Ito et al., 2012; Ma & Abdulai, 2016) and credit access (Peng et al., 2022), but the effect is stronger for small-scale farms. Some of these cooperatives even promote environmental sustainability by inducing the adoption of organic soil amendments (Tabe-Ojong, 2022).

With regards to contract farming, some studies have demonstrated that contract farming improves vertical integration and welfare outcomes (Mishra et al., 2018; Dubbert, 2019). In Benin, Maertens & Velde (2017) show that contract farming improves income, production and commercialization for rice farmers. Dubbert (2019) highlights that cashew contract farming increases labor productivity, price margins and net revenues in Ghana. In Nepal, tomato and lentil contract farming has been shown to improve yield and market performance, but negatively affect employment (Mishra et al., 2018) and variable and transportation costs (Mishra et al., 2018b). Bellemare & Novak (2017) show that contract farming improves food security and reduces hunger periods in Madagascar, while in India, Paltasingh & Jena (2023) point out that contract farming enhances technical efficiency, improves input quality and production technology for wheat growers.

In Ethiopia, cooperatives and contract farming are the two farm institutional arrangements that have been theoretically and empirically debated (Abebaw & Haile, 2013; Biggeri et al., 2018). Farmer cooperatives in Ethiopia have a long and turbulent history dating back to the early 1960s during the Imperial era (1930–1974), and these remained active during the Derg regime (1974–1991). During these early periods, cooperatives in Ethiopia were characterized by a coercive top-down approach that forced farm households to join cooperatives and put individual land holdings under the control of cooperatives (Bernard et al., 2008). Despite cooperatives' negative experiences and eventual dissolution in the 1990s, it has regained a central thrust since 1994 with the government's renewed interest in cooperatives to boost farmers' productivity and marketing (Bernard et al., 2008, 2013).

Contract farming also emerged in Ethiopia to enhance vertical integration and commercialization (Melese, 2010). It has mainly unfolded with the government's Growth and Transformation Plan II, which recognizes contract farming as a key element of the strategy to link small-scale farmers to sustainable market outlets and promote commercial farming (Hotland, 2017; Biggeri et al., 2018). Contract farming is also more commonly observed for cash crops and profitable value chains such as sesame, malt barley, horticultural crops and sugarcane (Mulatu et al., 2017; Bezabeh et al., 2020), although this has recently expanded to include staple crops such as wheat (Biggeri et al., 2018).

The extensive literature on the implications of cooperatives in Ethiopia yields mixed results. Bernard et al. (2008) show that agricultural marketing cooperatives obtain higher prices for their members, but this is not necessarily associated with commercialization. Using national level data, Bernard & Spielman (2009) illustrate that poorer farmers tend to be excluded from marketing cooperatives, particularly in the decision-making process. Bernard & Tafesse (2012) also demonstrate that cooperatives engage in a variety of activities that interfere with their ability to commercialize their members' surplus output. Francesconi & Heerink (2011), on the other hand, show that marketing cooperatives lead to a higher commercialization rate. Other studies by Abebaw & Haile (2013) and Getnet & Anullo (2012) indicate that agricultural cooperatives improve agricultural input adoption and livelihood among cooperative users.

Regarding contract farming, Bezabeh et al. (2020) and Ganew et al. (2022) reveal that contract farming is associated with increased farm income for malt barley farmers. These insights were earlier highlighted by Mulatu et al. (2017) who show that contract farming improves the income of vegetable producers. Beyond these profitable value chains, Biggeri et al. (2018) also illustrate that a contract farming approach linking wheat farmers to the pasta industry largely improves the gross and net income of farm households.

2.2 | Cluster farming in Ethiopia

Cluster farming is defined as a concentration of agricultural activities that generate income and employment opportunities in and around a specific area (Porter, 1998; Galves-Nogales & Webber, 2017). It is also defined as "a concentration of producers, agribusinesses, and institutions engaged in the same agricultural or agro-industrial subsector that links together and builds value networks while addressing common challenges and pursuing shared opportunities" (Galvez-Nogales, 2010, p.17). In Ethiopia, cluster farming involves about 30–200 smallholder farmers with adjacent farm plots who voluntarily pool a portion of their land to benefit from targeted government support and cluster economic agglomeration (ATA, 2019a; Tabe-Ojong & Dureti, 2023). Farm households participating in the clusters are required to contribute at least 0.25 ha of land, and the cumulative land per cluster must be at least 15 ha to harness the full benefits of participation. In these clusters, farmers commit to cultivating cluster priority crops and adhere to the best farm agronomic recommendations. Beyond farmers, this approach involves many stakeholders directly or indirectly at each stage along the cluster crop value chain (research, inputs, production, transportation, storage, marketing, and consumption) and fosters backward and forward-linkages (ATA, 2019b). Cluster households are expected to benefit from economies of scale such as greater affordability of modern technology (e.g., sharing the overhead costs of purchasing tractors), stronger bargaining power (e.g., negotiating favorable prices for their products), and stronger market linkages to serve bulk buyers or a large-scale buyer (e.g., contract farming with large processors) (Louhichi et al., 2019; ATA, 2019b).

The cluster farming approach differs from previous cooperatives and contract farming in three main ways. First, the approach fosters government alignment of development policies and strategies with agro-climatic and ecological conditions, which aims to encourage specialization and economies of scale at the local level and production diversification at the national level based on comparative advantage (MoFED, 2010; Louhichi et al., 2019; ATA, 2019b). Second, although it promotes market orientation like cooperatives and contract farming, cluster farming takes a broader approach that aims to integrate efforts that benefit smallholder farmers as well as other value chain actors through a market-driven and geographically-based approach (Louhichi et al., 2019). The cluster approach also entails both horizontal and vertical integration by encouraging the marriage of cooperative and contract farming initiatives. For instance, one of the program's primary goals is to vertically connect clusters to Integrated Agro-Industrial Parks (IAIP) and agribusiness firms (large traders, processors, and exporters) (ATA, 2019b). This link can boost private sector participation in cluster priority crops, with an ultimate focus on processing and value addition to ensure specialization, diversification, continuous raw material supply, and rural development.

Finally, cluster farming is a multi-stakeholder program that brings together diverse funders and implementers from the public, private, and development sectors to advance priority interventions in key commodity value chains. These stakeholders are involved in cluster farming through cluster-level value chain alliances, and regional and federal transformation councils, which are broad multi-stakeholder platforms that bring together key value chain actors for each commodity in order to govern and coordinate program implementation (ATA, 2019b). These stakeholders include federal government institutions (Ministry of Agriculture, Federal Cooperative Agency, Ethiopian Agricultural Transformation Agency, Agro-Industrial Parks), regional institutions (Regional Agricultural Bureaus, Regional Cooperative Bureaus, Regional Research Institutions), private sectors (Input Dealers, Banks), NGOs, Farmer Organizations (Cooperatives, Unions), and others (ATA, 2019b). Clusters also serve as a platform and mechanism for integrating and implementing various interventions across crop value chains such as input projects (improved seeds, agrochemicals and fertilizers, soil information systems (EthioSIS), Input voucher sales systems (IVSS), Cooperative Storage, the 8028 Farmer Hotline, contract farming, and marketing, among others (ATA, 2019a; ATA, 2019b).

2.3 | Cluster farming and commercialization in Ethiopia

The conceptual framework used here (Figure 1) assumes that farm households make the choice to participate in cluster farming. Their decision is based on the anticipated benefits from joining the cluster and resource constraints (e.g., land to contribute for cluster farming). This decision-making process can be represented in two stages. First, the household decides whether to participate in cluster farming. In the second stage, participating households determine the actual amount of land to contribute to cluster farming. Given that participation is voluntary, it is anticipated that households who are willing to join cluster farming choose to participate and contribute a certain plot size unless limited by a lack of resources. On the other hand, households that are unwilling to join cluster farming contribute no land. At the outcome level, cluster farming participants and non-participant farm households are

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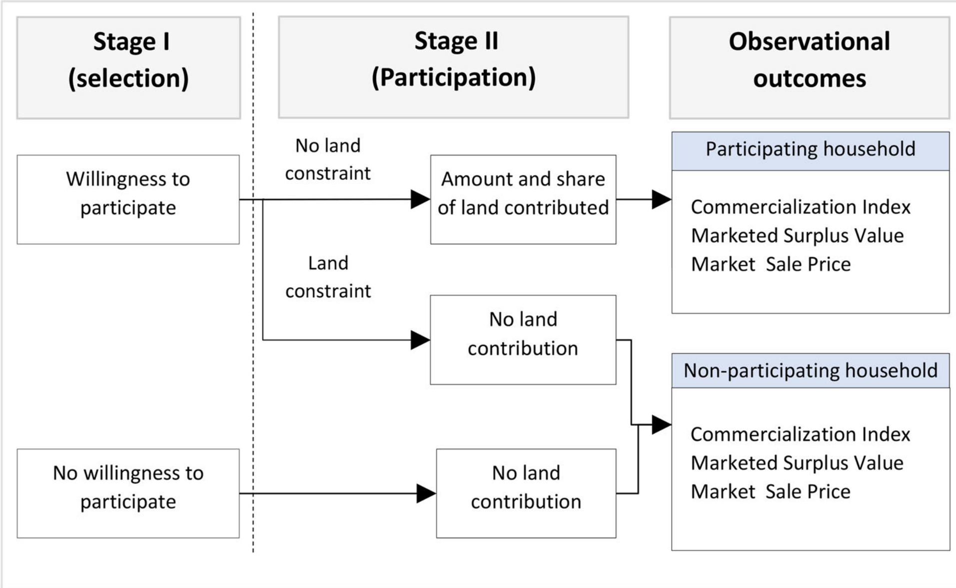

FIGURE 1 Cluster farming participation stages and commercialization outcomes[1] .

expected to achieve varying levels of commercialization outcomes. In this study, we specifically use the CI, MSV, and MSP as proxy variables to measure smallholder commercialization (detailed in Section 4.2). Related studies also use similar indicators to measure smallholder commercialization (e.g., Bernard et al., 2008; Fischer & Qaim, 2012; Fischer & Qaim, 2014; Woldeyohanes et al., 2017; Carletto et al., 2017; Tabe-Ojong et al., 2022a). We summarize the participation mechanism and outcomes in Figure 1.

Some empirical studies on geographic-based rural programs document the benefits of agro-clusters in terms of improving networks and partnerships, marketing access and economies of scale. Joffre et al. (2019, 2020) highlight that agro-clusters increase interaction and cooperation among cluster farmers by building trust and fostering networks and partnerships between farmers and other supply chain actors. Galvez-Nogales (2010) indicates that agro-clusters foster horizontal, vertical, and supportive interactions of farmers and other value chain actors to create synergies, enable competition, enhance access to services, and mitigate various sources of risk. Montiflor et al. (2015) show that vegetable agro-clusters improve institutional markets and market information and linkages in the Philippines. By examining clusters in the United States, Goetz et al. (2004) demonstrate the profitability and productivity implications of clusters for smallholders through countervailing market power and offering regions a source of competitive advantages. In India, the "Hub-and-spoke" cluster model has been touted as a way of strengthening backward integration linkages that create greater agglomeration economies in ways that support smallholder farmers and provide stable inputs to Agro-Industrial Parks (AfDB, 2018). Furthermore, agro-clusters have also been shown to increase smallholder production and productivity with ensuing impacts on poverty reduction in Indonesia and Ethiopia (Wardhana et al., 2017; Tabe-Ojong & Dureti, 2023).

3 | DATA AND VARIABLE MEASUREMENTS

3.1 | Household survey

The data used in this study come from a large-scale farm household survey conducted in February 2020 and April 2021 in Ethiopia. The survey included farm households producing Ethiopia's main staple crops such as wheat, maize, teff, barley, and sesame in four major regions (Amhara, Oromia, Southern Nations, and Tigray). In 2020, approximately 1.32 million smallholder farmers registered as members of cluster farming, with Amhara, Oromia, SNNPR, and Tigray sharing 0.29, 0.44, 0.14, and 0.13 percentage points, respectively (ATA, 2019a.). In terms of cluster priority crop distribution, 39.1%, 36.6%, 14.8%, 7.55% and 3.01% of these households grow wheat, maize, teff, malt barley and sesame, respectively. The two rounds of surveys were conducted as part of the assessment of the performance of cluster farming during both periods.

For the sample strategy, a multistage sampling technique was used to select households in the two survey

[1] In this study, we are interested in the second stage farm household decision and subsequent outcomes.

periods. In the first stage, 75 treatment and control woredas were randomly selected proportional to size. Woredas where cluster farming has been promoted are our treatment woredas, whereas woredas where cluster farming does not exist at the time of the survey form our control woredas. The treatment and control woredas are similar in terms of farming systems and practices and crops cultivated; they also belong to similar agro-ecological zones, except that cluster farming has not been promoted in the control woredas. In fact, some of the control woredas are areas where the government intends to scale up the cluster approach, but at the time of the survey, no clusters have been established. From these 75 woredas, kebeles were randomly selected, and households were further randomly selected for interviews.[2] In total, we reached 3978 households over the two survey periods, but due to some missing entries, we only used 3969 households in the analysis.

The interviews were carried out by a group of well-trained enumerators. The survey was designed and administered on survey-based tablets, which enabled real-time quality checks and controls. All activities were conducted, administered, and supervise by the Ethiopian Agricultural Transformation Agency. The surveys captured information on the household socioeconomic characteristics and value chain activities. Specifically, the survey included household socio-demographic characteristics (gender, age, education, and family size), household farm assets (land size, off-activities, total production, and market surplus output), and its social network (neighbor participation in cluster farming, awareness, and membership in self-help groups). Information was also captured on access to extension services and credit.

Although we have two-period data, these data cannot be treated as a panel since different households were interviewed in each year, so we treat our data as cross-sectional. However, we include year dummies in all regressions to control for year effects. We also add regional dummies and clustered standard errors at woreda level to account for agro-ecological and farming system differences in the study sites. To reduce issues of endogeneity and robustify the analysis, we also construct a pseudo panel by aggregating the household level data to the kebele level.

3.2 | Measurement of commercialization

Household commercialization can be measured both as a binary decision of the household to participate in output markets and as the actual sales intensity conditional on market participation (Woldeyohanes et al., 2017; Tabe-Ojong et al., 2022a). Utilizing binary decisions as a commercialization outcome measurement produces less insights, especially in the context where most households are expected to participate in output markets. In this study, we use three outcome variables to proxy smallholder commercialization: MSP, MSV, and CI. MSP seeks to determine the extent to which cluster farming improves market conditions for farm households through higher output prices. Specifically, we are interested in assessing whether participation in cluster farming enables farm households to obtain higher market prices for their outputs by lowering transaction costs, increasing bargaining power, and reaching out to more appealing markets, among others. MSP is simply measured as the household level average price in ETB at which households sell cluster farming priority crop output in the local market.

MSV and CI measurements indicate farm households' actual response to improved prices in output markets in terms of the actual amount of output and share of output marketed, respectively. MSV shows the exact total amount of output marketed, but it does not help to compare the degree of output marketed by different farm households. Also, MSV says little about the real commercialization level of households since it is not based on the quantity harvested. For instance, let us say two households harvest 1000 and 500 kg of barley, respectively, and both farmers sell 500 kg. By measurement of MSV, each farmer appears to have similar commercialization intensities. However, if we compare the actual quantity harvested, the second farmer has a higher sales intensity than the first given that he sold all he harvested. To take this into account, we use the share of the output commercialized, the ratio of sales to production/harvest, which we define as the CI. CI is utilized as a standard measure of household commercialization in other related studies (e.g., Bernard et al., 2008; Woldeyohanes et al., 2017; Tabe-Ojong et al., 2022a). This measure bounds the value of commercialization to be between 0 and 1 and enables comparison across households. Therefore, we use CI as our outcome variable of interest in this study. MSP and MSV were originally measured in ETB, but we converted them to USD purchasing power parity using the 2017 International Comparison Program conversion rates.

3.3 | Measurement of cluster farming

We measure cluster farming using three different proxies capturing extensive and intensive measures of participation. The first measurement is a dummy for cluster farming participation that assigns a value of one to households that

[2] From these 75 woredas, 1–5 kebeles were randomly selected (in total 360 kebeles) from which households were further randomly selected for interviews.

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participate in cluster farming and a value of zero to those that do not. The second measurement is the amount of land allocated to cluster farming. Cluster farming requires households to contribute at least 0.25 hectares of land and grow cluster priority crops. However, using the amount of land allotted to a cluster does not allow for comparisons between households. The alternative, third variable is the share of total land contributed, which depends on the total landholding. The share of land contributed ratio varies between 0 and 1 and enables comparison across households.

4 | METHODOLOGY

4.1 | Empirical specification

Our empirical strategy is based on the random utility framework, where a representative household participates in cluster farming to maximize its underlying utility. Households will participate in cluster farming if the expected net benefit from participation is greater than non-participation, as shown in the following model:

$$C_i^* = \theta Z_i + \mu_i, \text{ with } C_i = \begin{cases} 1 & \text{if } C_i^* > 0 \\ 0 & otherwise' \end{cases} \quad (1)$$

C_i^* is a latent variable indicating the utility difference between cluster farming participation and non-participation; C_i is an observable binary variable that takes the value 1 if a household is a cluster farming participant and 0 otherwise; Zi is a vector of exogenous variables, θ is a vector of parameter estimates, and μ_i is stochastic error term that represents the unobservable part of a smallholder utility function. Based on this, the probability that a smallholder farmer participates in cluster farming is derived and estimated as follows:

$$P_r\ (C_i = 1) = P_r\ (C_i^* > 0) = P_r\ (\mu_i > -\theta Z_i) = 1 - F(-\theta Z_i) \quad (2)$$

Following Ma & Abdulai (2016) and Tabe-Ojong (2022), the cluster participation decision is linked to the resulting outcomes by further assuming that a rational smallholder aims to maximize their commercialization outcomes from participating in cluster farming (Y), as shown below:

$$Y_{max} = PQ(S, Z) - SW \quad (3)$$

where P is the price of commodity cultivated in clusters; Q is harvest supply to the market; W is a vector of production inputs (e.g., land); S is a vector of input prices; and Z is a vector of explanatory variables. The commercialization outcomes can be specified as a linear function of the choice of cluster farming participation, resource endowment and other relevant household and farm-level characteristics:

$$Y_i = M_i\, \partial + C_i \gamma + \in_i \quad (4)$$

where Y_i represents the three outcomes of CI, MSV, and MSP; M_i is a vector of household and farm level explanatory variables; C_i is a dummy variable for cluster participation choice; ∂ and γ are the parameter estimates; and $\in_i$ is the error term.

4.2 | Identification strategy

If participation in cluster farming (C_i) is exogenous, the relationship of cluster farming and commercialization outcomes can be directly estimated using the naïve ordinary least square (OLS) model. However, farm households self-select into cluster farming depending on various observable and unobservable characteristics. Failure to account for these underlying factors may lead to inconsistent and biased estimates. There are four potential sources of bias commonly identified in extent related literature: unobserved and observed heterogeneity, measurement error, reverse causality, and spill-over effects (e.g., Godtland et al., 2004; Bernard et al., 2008; Fischer & Qaim, 2012; Tabe-Ojong & Dureti, 2023).

Regarding heterogeneity, in addition to observable differences, participants and non-participants may also differ significantly in the distribution of their unobservable characteristics (e.g., ability, risk preference). These factors may be related to participation outcome or error terms in both selection and outcome equations resulting in "selection on unobservables." Given our cross-sectional data, it is difficult to satisfactorily control for this eventuality beyond including different controls and observing the stability of the coefficients. However, to minimize these biases, we employ ESR and IV estimators, which are commonly used to deal with these selection biases in cross-sectional data settings (e.g., Shiferaw et al., 2014; Tabe-Ojong., 2022). The ESR is a two-tiered model with one selection equation and two outcome equations. The selection equation is based on the binary decision of household participation in cluster farming and the determinants of that decision. The two outcome equations represent the association of cluster farming and outcomes of interest based on two regimes of participants and non-participants. For a full description of the model, please confer Lokshin and Sajaia (2004).

For the case of measurement error, although it is always challenging to claim data accuracy, we are confident that cluster participation was well captured with the actual amount of land allocated by farmers since these processes are well supervized and monitored. The data collection process was also supported by GPS techniques, which were captured during data collection. In the case of reverse causality between cluster farming and commercialization outcomes, allocating more land to clusters may increase commercialization through economies of scale advantages that enhance smallholders' bargaining power and ease market access for input purchases and output sales. Households that are generally enjoying more commercialization benefits may allocate more land than others. However, land is a limited resource in Ethiopia, and an increase in commercialization may not lead to the allocation of more land. There may be little or no land allocation for households that allocate most or all their lands to cluster farming, which restrains reverse causality threats (Tabe-Ojong & Dureti, 2023). However, we employ ESR and IV approaches with the specification of two exclusion restrictions to control for any residual endogeneity issues. The two exclusion restrictions are household awareness of the existence of cluster farming and neighbor participation in cluster farming.

Previous studies used both household awareness and neighbor participation as instruments in similar contexts (e.g., Ito et al., 2012; Tabe-Ojong & Dureti, 2023). However, we motivate how our instruments may satisfy the three IV conditions: relevance, exogeneity and exclusion restriction. Cluster farming is a novel concept in the study area, and hence understanding its existence and operation is required for participation, but knowing about clusters per se is not expected to affect commercialization outcomes except through participation in the clusters. Neighborhood participation also facilitates information flow and may affect household participation decisions. Ito et al. (2012) show that neighboring farmers' choice of participation in local community initiatives is positively and significantly related to their neighbor's membership. However, there is no reason to believe that neighbor participation per se affects commercialization outcomes unless the farm household participates. In the relevance condition, both awareness of cluster farming and neighbor participation variables are significantly correlated with cluster farming participation (with R^2 = 29.32% and joint F-statistic significant at 1%). This finding validates the instruments based on the relevance condition (refer to Appendix A1b). With regards to the exclusion restriction condition, it is intuitive to assume that awareness and neighbor participation affect commercialization only through cluster farming participation since these variables are entirely about knowing the existence of cluster farming and observing the participation of neighbors.

Examining the third condition of instrument validity, exogeneity, requires the valid instruments to be uncorrelated with the error terms to meet exogenous claims (Schmidheiny, 2016). Generally, good instruments should involve some form of randomization to be able to induce an exogenous variation for causal claims, but there is no formal way to empirically test the exogeneity of the instruments apart from theoretically motivating them. However, given that we have two instruments, we conduct some tests including the overidentification tests. First, we perform a simple falsification test following Di Falco et al. (2011). In this case, we run a probit model on the selection equation to see if the instruments are strongly correlated with the binary participation decision. Then, we estimate the OLS model with the outcome variables of non-participants if instruments are significant in the first condition. The results show an insignificant correlation with outcomes. For the overidentification tests, we perform Wooldridge's score test of overidentifying restrictions, which is heteroskedasticity-robust (Wooldridge, 1995). Similarly, statistically insignificant estimates are obtained in this case. Thus, we fail to reject the null hypothesis that the instruments are valid. Based on these results, our instruments could be argued to be as good as random, but we are wary of making causal claims given the limitations of our cross-sectional data.

Finally, there could be diffusion or spill-over effects, where the treatment effect of participants significantly affects the outcome of non-participants. In the presence of such effects, comparing participants to non-participants in the neighboring area may likely underestimate the effect of participation. While addressing the spill-over effect is not always easy, we assume this is not much of an issue in this analysis. This is because most non-participants are from different woredas than participants, which implies less possibility of interaction between the two groups due to a geographic distance barrier. To further minimize any residual endogeneity issues, we also use a sub-sample of households in different woredas in our dataset as a robustness check.

4.3 | Pseudo-panel analysis

Given that we have a repeated cross-sectional data, we apply a pseudo-panel method to minimize endogeneity concerns and robustify the analysis. The pseudo panels are created by grouping the individual observations into a number of stable groups (i.e., cohorts) on the basis of their observable time-invariant common characteristics such as geographic location, land size, birth date, etc. (Verbeek, 2008; Heshmati & Kumbhakar, 2008; Guillerm, 2017). Guillerm (2017) defines a good cohort selection criterion for pseudo panel construction as a characteristic that does not change over time for individuals, is observable for all the individuals, and forms large enough cohorts without losing much variability. Following this credence, we construct pseudo panel data by aggregating farm level data to the kebele level. These kebeles are then used as the unit of analysis in addition to the main household level analysis.

Formally, we aggregate all observations at t year and k kebele by linearly transforming the initial Equation (4) as follows:

$$Y_{kt}^{*} = M_{kt}^{*}\,\partial + C_{kt}^{*}\gamma + \epsilon_{kt}^{*} \quad k = 1, \ldots, K; t = 1, \ldots, T \tag{5}$$

where each variable S is measured as $S_{kt}^{*} = \frac{1}{n_{kt}} \sum_{i \in k,t} S_{it}$

Here we estimate the observed average values for the individuals in the sample belonging to the kebele. Given the linear transformation, the pseudo-panel model (5) has linear parameters and can thus be estimated using standard panel estimation techniques for panel data. Heshmati & Kumbhakar (2008) show that depending on whether one treats the kebele-specific effects as fixed or random, a pseudo-model can be estimated either by the least-squares dummy variable approach (fixed effects model) or the generalized least-squares method (random effects model). In this article, we estimate both FE and RE models. For RE, we follow Woldeyohanes et al. (2017) and Tabe-Ojong et al. (2022b) to apply a flexible extension of the random effect estimator known as the correlated random effect (CRE), which provides FE estimates for the time-invariant heterogeneity, while avoiding the incidental parameters problem. To do so, we include the vectors of within-kebele means for the time-varying independent variables.

4.4 | Heterogeneity analysis

Smallholder participation in cluster farming may exhibit a heterogeneous relationship with different commercialization outcomes based on household farm size. Smallholders with larger landholdings are more likely to participate in cluster farming as they have more land to allocate and are likely to reap more benefits due to production economies of scale. Estimating average results may hide considerable heterogeneity across households, which may imply some form of inequality in rural settings. Moreover, understanding the heterogeneous effect of cluster farming may also help in policy development to identify policy options that meet the needs of a more diverse socioeconomic group of households as well as minimize the possible negative effects on the most vulnerable groups. To assess this relationship, we run regressions with three different farm structures following Ma & Abdulai (2016) and Tabe-Ojong et al. (2022c) . These farm sizes range from small (≤1 ha) to medium (1 < ha <5) to large (≥5 ha) scale farms. In addition to this, we further perform some heterogeneity analysis based on the crop type. This is to capture crop-specific differences in the outcome variables (commercialization, marketed surplus, and market price) given that some crops such as maize, teff and wheat are staples which are used for home consumption and eventually marketed, while others (such as malt barley and sesame) are mainly commercial crops.

5 | RESULTS AND DISCUSSION

5.1 | Descriptive analysis

The summary statistics of all variables used in this study are presented in Table 1. On average, the total income from the total marketed surplus is 729 USD. This measures the total value of outputs marketed by the household after meeting household consumption demands. The CI, the percentage of total output marketed, is on average about 56%. The average village level price per 100 kgs of all crop output is about 56.5 USD. Regarding participation in cluster farming, about 57% of households in the study area participate in clusters, where they allocate an average of 0.60 hectares of land to the cluster. There are about 17 household members per cluster, and the total land per cluster is about 12 hectares. Among the household socioeconomic characteristics, the average age of the household head is 43 years. Most households are male-headed with an average family size of six members and, on average, 73% of households have achieved primary education. Average total landholdings are about 2.3 hectares, where households allocate a share of 0.28 to the cluster. Looking at households with different farm sizes, while about 30% of households own land sizes less than 1 hectare, about 60% of household farm sizes range between 1 and 5 hectares. This shows that most households are smallholder farmers, although this is larger than the national average of 1 hectare per household. Regarding institutional factors, extension access in the study area is widespread (90%), and 33% of household heads have access to credit facilities.

Awareness about cluster farming is relatively high with about 85.65% of households reporting to have a clear understanding of cluster farming and how it operates. According to the survey, households learn about cluster farming from three primary sources: government official promotion, development agent (DA) campaigns, and interactions with neighboring participating households. The dummy for neighbor participation refers to whether a household is aware of their neighbor's participation in cluster farming. On average, 23% of households are aware of their neighbor's participation in cluster farming.

To understand observable differences between households based on cluster farming, we performed a mean difference test as shown in Table 1 (column 4). Signifi-

TABLE 1 Summary statistics.

Variables	(1) Full sample	(2) Treatment	(3) Control	(4) (2)-(3)
Outcome variables				
Commercialization Index (0–1)	0.56 (0.32)	0.59 (0.30)	0.52 (0.34)	0.00*** (0.00)
Market surplus value (USD)	729 (1515)	925 (1868)	469(771)	457*** (0.00)
Market sale price (USD)	56.5 (30.7)	57.6 (30.4)	55.1 (31.0)	2.5** (0.01)
Variables of interest				
Cluster farming (dummy)	0.57	1.00	0.00	1.00
Land allocated to cluster (hectares)	0.60 (0.87)	1.06 (0.93)	0.00 (0.00)	1.06*** (0.00)
Plot allocation ratio (0–1)	0.28 (0.31)	0.49 (0.26)	0.000 (0.00)	0.49*** (0.00)
Control variables				
Total cluster size (hectares)	11.5 (16.9)	20.1 (18.1)	0.00 (0.0)	20.1*** (0.00)
Cluster members size (number)	16.6 (24.6)	29.2 (26.3)	0.0 (0.0)	29.2*** (0.00)
Age of household head (years)	42.7 (11.0)	42.0 (10.2)	43.6 (11.9)	1.6*** (0.00)
Education (dummy)	0.73	0.81	0.62	0.19***
Female head (dummy)	0.10	0.11	0.09	0.02**
Household size (number)	6.5 (2.4)	6.6 (2.4)	6.3 (2.5)	0.3*** (0.00)
Landholding (hectares)	2.3 (2.0)	2.5 (2.2)	1.9 (1.5)	0.7*** (0.00)
Group member (dummy)	0.38	0.39	0.36	0.03*
Credit access (dummy)	0.33	0.51	0.12	0.39***
Extension (dummy)	0.91	0.97	0.81	0.16***
Storage (dummy)	0.60	0.67	0.50	0.18***
Off-farm income	0.41	0.43	0.37	0.06***
Wheat (dummy)	0.30	0.30	0.29	0.01
Teff (dummy)	0.14	0.14	0.14	0.00
Sesame (dummy)	0.07	0.06	0.09	0.03***
Malt Barley (dummy)	0.14	0.15	0.14	0.01
Maize (dummy)	0.35	0.35	0.34	0.00
Neighborhood participation (dummy)	0.23	0.24	0.21	0.04***
Cluster awareness (dummy)	0.78	0.96	0.54	0.42***
Observations	3969	2263	1706	

Note: Columns (1), (2), and (3) present the sample means (proportions when % is shown in the variable name or in the table) of selected variables for the full sample, the treatment group and the comparison group, respectively. Standard deviations in parentheses. Column (4) presents the mean difference between the treatment and comparison groups. *P*-value of the corresponding *t*-test in parentheses. Significance stars: $^*p \leq .1$, $^{**}p \leq .05$, $^{***}p \leq .01$.

cant differences are observed between households in terms of MSV and CI, with cluster members commercializing more compared to non-members. Regarding farm households' socioeconomic characteristics, cluster participant households are led by the younger and relatively more educated heads of households, with the difference being significant at 1%. Households in clusters generally have more landholdings. Farming cluster member households also have better access to credit and extension institutional facilities.

Overall, the mean comparison between two groups suggests significant observable differences in terms of household socio-economic characteristics and outcome variables. However, these mean differences do not consider confounding factors. In the following part of the article, these differences are further examined using a rigorous econometric model to test whether these differences remain after controlling for both observable and unobservable factors.

5.2 | Association of cluster farming and commercialization

5.2.1 | ESR Model result

In this section, we discuss the ESR estimates on the relationship between cluster farming and MSV, CI, and MSP.

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TABLE 2 ESR estimates of the effect of cluster farming on CI, MSV, and MSP.

Variable	Mean outcome		ATT	*t*-value
	Participant	Non-participant		
Commercialization index (CI)	0.579 (0.00)	0.476 (0.00)	0.102***	61.24
Market surplus value (MSV)	974.61 (17.31)	558.48 (10.3)	416.13***	38.96
Market sale price (MSP)	57.00 (0.66)	52.77 (0.62)	4.23***	35.02
	ATU			
Commercialization index (CI)	0.618 (0.00)	0.516 (0.02)	0.102***	54.24
Market surplus value (MSV)	690.13 (16.21)	468.76 (8.39)	221.37***	19.26
Market sale price (MSP)	58.48 (0.73)	55.11 (0.69)	3.37***	26.52

Note: Clustered standard errors at woreda level in parentheses; ***$p < .01$, **$p < .05$, *$p < .1$.

Unlike the simple mean differences presented in Table 1, these estimates account for selection bias resulting from both observable and unobservable characteristics. Table 2 shows the average treatment effect on the treated (ATT) and the untreated (ATU) in relation to the CI, MSV, and MSP.

These results show that participation in cluster farming has a positive and significant association with smallholder commercialization. The ATT shows participation in cluster farming is associated with increases in the CI by approximately 0.10 (21.01%), household MSV by 416 USD (74.51%), and MSP by 4.23 USD (8.02%) per year. Looking at the average treatment effect on the untreated, the results show positive and statistically significant results for all outcome variables. ATU shows effects on CI, MSV and MSP if the non-participating smallholders would have participated in cluster farming. The results show that CI would increase by 0.10 (19.62%) in such a scenario, while MSV and MSP would increase by 221.37 USD (47.22%) and 3.37 USD (6.12%) per year, respectively.

5.2.2 | IV Model result

The IV estimates of the association between cluster farming and commercialization outcomes are presented in Table 3. Here, we use the share of land allocated for cluster farming as a proxy measure of cluster farming. The signs and magnitudes of the estimated coefficients are similar for both ESR and IV regression models, which may already suggest the robustness of the findings. The IV estimates indicate that a 0.1 increase in the share of land allocated to cluster farming increases commercialization by approximately 0.21, household MSV by 622.7 USD and MSP by about 4.96 USD, respectively.

The positive association between cluster farming and smallholder commercialization shown in both ESR and IV models may be attributed to economies of scale advantages, horizontal and vertical linkages with value chain actors, and coordinated and targeted support from the government, NGOs, and the private sector. The positive relationships observed in this study are in line with previous empirical findings that cooperatives improve marketing conditions and output commercialization for farmers (Bernard et al., 2008; Barham & Chitemi, 2009; Francesconi & Heerink, 2011). For instance, our finding relating to market sales price is in accordance with Bernard et al. (2008) who find that members of agricultural marketing cooperatives obtain higher prices for their products in Ethiopia. However, unlike Bernard et al. (2008), we find a significant association between cluster farming and commercialization. On the other hand, consistent with our finding, Francesconi and Heerink (2011) shed light on the fact that marketing cooperatives in Ethiopia lead to higher commercialization rates for their members. Similarly, our result of a positive relationship between cluster farming and commercialization is also in consonance with Barham & Chitemi (2009) for Tanzania, who show that cooperatives improve market performance.

In addition, our finding is consistent with other literature on contract farming, which shows that vertical integration initiatives improve marketing conditions for farm households (Maertens & Velde, 2017; Biggeri et al., 2018; Mishra et al., 2018; Dubbert, 2019). Our result is in line with Biggeri et al. (2018) who indicate that contract farming provides a better market link for wheat farmers in Ethiopia. We also obtain consistent results with Maertens &Velde (2017) who indicate that contract farming improves commercialization for rice farmers in Benin. Similar results are also obtained by Mishra et al. (2018, 2018b) for Nepal and Dubbert (2019) for Ghana. Our finding also provides credence for other studies that highlight the positive role of agro-clusters in improving market conditions and farmer welfare (e.g., Montiflor et al., 2015; Wardhana et al., 2017; Joffre et al., 2019; Joffre et al., 2020; Tabe-Ojong & Dureti, 2023).

Overall, our results are in the same direction, enabling us to conclude that participation in cluster farming plays a significant role in improving the transformation of smallholder farmers from subsistence agriculture to com-

TABLE 3 IV estimates of the effect of cluster farming on CI, MSV, and MSP.

	Commercialization index	Market surplus value	Market sale price
Cluster-farming (0-1)	0.21***	622.7***	4.96*
	(0.07)	(178.06)	(2.93)
Additional controls	Yes	Yes	Yes
Crop dummies	Yes	Yes	Yes
Region dummies	Yes	Yes	Yes
Time controls	Yes	Yes	Yes
Woreda FE	Yes	Yes	Yes
R squared	0.11	0.10	0.88
Observations	3344	3344	3344

Note: Clustered standard errors at woreda level in parentheses; ***$p < .01$, **$p < .05$, *$p < .1$. Additional controls include the age and educational level of the household head, gender of the household head, household size, landholding, group membership, access to credit, storage and extension services. The controls are included to increase the precision of the regression estimates. The instrumental variables are the neighbor's participation in cluster farming and awareness of the existence of cluster farming.

TABLE 4 CRE and FE estimates of the effects of cluster farming on CI, MSV, and MSP.

	(1) Commercialization index		(2) Market surplus value		(3) Market sales price	
Variables	FE	CRE	FE	CRE	FE	CRE
Cluster-farming (0–1)	0.031	0.079	1050.578**	845.927**	49.710**	28.669**
	(0.277)	(0.173)	(535.171)	(429.066)	(20.81)	(14.47)
Observations	324	324	330	330	330	330
Number of kebele	165	165	165	165	165	165
Additional controls	No	Yes	Yes	Yes	Yes	Yes
Woreda FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	No	No	No	Yes
Instrumental variable	Yes	Yes	Yes	Yes	Yes	Yes

Note: Clustered standard errors at woreda level in parentheses; ***$p < .01$, **$p < .05$, *$p < .1$. Additional controls include the age and educational level of the household head, gender of the household head, household size, landholding, and group membership. The instrumental variables are the neighbor's participation in cluster farming and awareness of the existence of cluster farming.

mercialization by significantly improving CI, MSV, and MSP. Thus, cluster farming may enable farmers to aggregate produce, reduce transaction costs and diseconomies of scale, and overcome constraints to participating in higher-value markets and contract farming schemes, and consequently improve market outcomes. However, while our results establish the positive contribution of cluster farming in general, we caution against interpreting the magnitude of the estimates at face value.

5.2.3 | Pseudo-panel result

For pseudo-panel results, as shown in Table 4, our core results on the relationship between cluster farming and smallholder commercialization are maintained as we find a positive association between cluster farming and commercialization outcomes. The results are also similar for both FE and CRE models. However, we find a positive but insignificant relationship between cluster farming and CI. These additional sets of results further strengthen the analysis and bolster our claim on the positive relationship between cluster farming and smallholder commercialization. At this point, we mention two limitations with the pseudo panel that may well explain the slightly nuanced difference with the cross-sectional estimates. First, kebeles in the Tigray region were not part of the second-round survey because of the conflict in the northern part of the country. Second, some of the kebeles in other regions visited during the first round were not covered in the second-round survey. Thus, new kebeles were visited in the second round, making it hard to obtain a balanced kebele panel.

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TABLE 5 ESR estimates of effect heterogeneity by farm size.

Variable		Mean outcome: Participant	Mean outcome: Non-participant	ATT	*t*-value
Commercialization index (CI)	Small (≤ 1 ha)	0.507 (0.01)	0.469 (0.01)	0.038***	5.94
	Medium (1 to 5 ha)	0.582 (0.00)	0.459 (0.00)	0.122***	65.33
	Large (≥5 ha)	0.709 (0.01)	0.500 (0.02)	0.208***	14.48
Market surplus value (MSV)	Small (<1 ha)	370.35 (11.37)	225.96 (6.41)	144.38***	18.37
	Medium (1 to 5 ha)	1004.92 (17.41)	476.04 (8.43)	528.88***	37.35
	Large (≥5 ha)	2219.35 (100.66)	1034.01 (74.11)	1185.34***	13.27
Market sale price (MSP)	Small (≤ 1 ha)	56.31 (1.36)	50.24 (1.12)	6.07***	13.46
	Medium (1 to 5 ha)	55.97 (0.78)	51.35 (0.76)	4.62***	36.6
	Large (≥5 ha)	65.09 (2.42)	58.85 (2.47)	6.24***	9.63

Note: Clustered standard errors at woreda level in parentheses in parentheses; ***$p < .01$, **$p < .05$, *$p < .1$.

5.3 | Results on the effect of heterogeneity

This section discusses our results from a heterogeneity analysis based on farm holding size and crop types. First, disaggregating households by farm size, we look into a cluster farming association with smallholder commercialization for households with different farm sizes. As summarized in Table 5, cluster farming benefits households with medium and large farm sizes more than those with a small farm size (see Appendix A4 for IV result). Although this indicates these households can contribute more land to cluster farming and reap available opportunities, it also implies small size household benefits less as they have little to no plot land to contribute to cluster farming. The result also indicates that medium size and large-scale farms benefit more both in terms of the share of output marketed and output marketed values. This finding is consistent with those of Bernard et al. (2008) and Bernard and Spielman (2009) who indicate that smaller farmers in Ethiopia tend to reduce their marketed output even with increased prices, only indirectly benefitting, whereas the opposite is true for larger farms.

On the other hand, our findings are not in consonance with Ma & Abdulai (2016) and Verhofstadt & Maertens (2015) who found that smaller farms tend to benefit more from cooperatives in China and Kenya. Similarly, our findings that medium size and large-scale farms benefit more than small scale farms both in terms of share of output marketed and output marketed values are not in line with the findings of Mishra et al. (2018) and Dubbart (2019) in Nepal and Ghana, respectively. They found that small farms tend to gain more profits. This implies that there are disparities in terms of cluster farming associations with commercialization on different scales of production across different countries. It also indicates that the magnitude of association is not homogenous across different farm sizes and location. Hence, there is a need for a more inclusive and targeted cluster farming model that also benefits marginalized communities. Nevertheless, the findings should also be interpreted with caution in cases where smallholders may overestimate, whereas large scale farmers tend to underestimate their land sizes (Carletto et al., 2013; Dubbart, 2019)

We also perform some heterogeneity analyses by disaggregating farm households based on the cultivated priority cluster crops. As shown in Table 6, the heterogeneity analysis reveals that cluster farming improves commercialization outcomes for all crops, albeit to varying degrees. Our findings are consistent with other studies in developing countries that argue that agricultural commercialization is not limited to cash crops since staple food crops can also be marketed (Pingali et al., 2005; Gebre-ab, 2006; Alemu et al., 2006; Gidelew et al., 2022). According to these studies, the production of a marketable surplus of staple foods over what is needed for one's own consumption is the most common form of commercialization. Given that we define agricultural commercialization as the proportion of agricultural production that is marketed regardless of crop type, our findings are reflective of the Ethiopian context, where the production and sale of staple crops are common.

5.4 | Additional robustness results

We perform some additional analysis to further confirm and corroborate our findings by using alternative measures of cluster farming. Using the amount of land allocated for cluster farming as another measure of cluster farming, we employ the IV estimator to estimate the relationship between cluster farming and commercialization outcomes.

Table 7 shows the result of IV estimates for the three outcome variables – CI, MSV, and MSP. The signs and mag-

TABLE 6 ESR estimates of the heterogeneity effect by crop types.

Variable		Mean outcome: Participant	Mean outcome: Non-participant	ATT	*t*-value
Commercialization index (CI)	Maize	0.597 (0.00)	0.563 (0.01)	0.034***	5.85
	Wheat	0.510 (0.01)	0.504 (0.01)	0.005	1.29
	Teff	0.616 (0.01)	0.335 (0.01)	0.28***	27.51
	Barley	0.537 (0.01)	0.333 (0.01)	0.204***	27.9
	Sesame	0.859 (0.013)	0.767 (0.02)	0.092***	3.55
Market surplus value (MSV)	Maize	600.91 (15.36)	589.96 (17.43)	10.94	0.96
	Wheat	1109.7 (38.15)	774.58 (24.98)	335.10***	19.11
	Teff	4049.5 (284.50)	465.90 (40.35)	3583.6***	12.5
	Barley	814.53 (33.11)	468.63 (24.64)	345.89***	15.42
	Sesame	698.63 (28.85)	−410.6 (34.53)	1109.2***	25.89
Market sale price (MSP)	Maize	26.69 (0.06)	26.77 0 (0.103)	−0.079	−0.85
	Wheat	59.64 (0.26)	47.52 (0.11)	12.13***	48.3
	Teff	105.05 (0.57)	92.09 (0.46)	12.95***	16.89
	Barley	55.29 (0.22)	53.38 (0.23)	1.92***	5.78
	Sesame	110.55 (1.84)	105.62 (0.98)	4.93***	5.01

Note: Robust standard errors are in parentheses; ***$p < .01$, **$p < .05$, *$p < .1$.

TABLE 7 IV estimates of the effect of Cluster Farming on CI, MSV, and MSP.

	Commercialization index	Market surplus value	Market sale price
Land allocated to cluster farming	0.14***	495.00***	3.83***
	(0.03)	(92.60)	(1.28)
Additional controls	Yes	Yes	Yes
Crop dummies	Yes	Yes	Yes
Region dummies	Yes	Yes	Yes
Time controls	Yes	Yes	Yes
Woreda FE	Yes	Yes	Yes
R squared	0.01	0.09	.
Observations	3700	3700	3700

Note: Robust standard errors are in parentheses; ***$p < .01$, **$p < .05$, *$p < .1$. Additional controls include the age and educational level of the household head, gender of the household head, household size, landholding, group membership, access to credit, storage and extension services. The instrumental variables are the neighbor's participation in cluster farming and awareness of the existence of cluster farming.

nitudes of the estimated coefficients using IV regression are similar to previous results, suggesting the robustness of our findings. The estimates show that participation in cluster farming significantly increases CI, MSV, and MSP by about .1, 740 USD and 13 USD, respectively. This allows us to maintain the result that participation in clusters has a positive relationship with smallholder commercialization .

Furthermore, using a subset of our data, we tested for the possibility of spillover effects. To that end, we divide farm households into control and treatment groups based on the woredas from which they are drawn. We assume that there is a sufficient geographic barrier between farm households from different woredas, implying that spillover effects are less likely in our sub-sample. Our findings confirm the existence of a positive relationship between cluster farming and commercialization outcomes (see Appendix 3A).

6 | CONCLUSION AND POLICY IMPLICATIONS

In this study, we examine the concept of cluster farming in relation to smallholder commercialization measured as CI, MSV and MSP. We use a large farm household survey from four Ethiopian regions where farming clusters are promoted and farm households are encouraged to cultivate priority crops such as maize, wheat, teff, barley, and sesame. We employ ESR and IV models robustified with a pseudo-panel model to account for both observed and unobserved heterogeneities that may be in the way of establishing these relationships.

Based on our results, the following key conclusions are drawn. To begin with, we conclude that participation in cluster farming enhances smallholder commercialization as shown by the significantly positive relationship between cluster farming and smallholder commercialization. Specifically, our ESR findings reveal that participation in cluster farming increases the CI by 21.01%, household MSV by 74.51%, and MSP by 8.02% per year. From the IV findings, it is revealed that a 0.1 increment in the share of land allocated to cluster farming is associated with an increase in commercialization by approximately 0.21, household MSV by 622.7 USD and MSP by about 4.96 USD. In terms of heterogeneity, we conclude that the association of cluster farming and smallholder commercialization is not homogenous. Rather, cluster farming has a heterogonous relationship with smallholder commercialization in terms of production scales and crops cultivated. Specifically, our findings reveal that the benefits of cluster farming are higher among medium and large farms. Similarly, participation in cluster farming is positive for households growing all crops, but the magnitude of the benefits varies to some degree.

The findings are robust to a pseudo-panel model and across different cluster farming measurements. In addition, our results are also in line with other studies on the role of cluster farming and other farm organizations in improving commercialization outcomes. Overall, despite the observed heterogeneous effects among various groups of households, our findings suggest that cluster farming is meeting its primary objective of improving farm household commercialization. Based on the findings of the impacts of commercialization on these aspects of rural households, we conclude that cluster farming could be a good policy option for easing smallholder farmers' entry into commercialization, particularly in developing countries.

The findings from this study have some relevant policy implications. First, the significant contribution of cluster farming to improving household commercialization should motivate policymakers to strengthen their efforts to encourage smallholder households to participate in cluster farming. This is further supported by the counterfactual finding that cluster farming has the potential to increase the market surplus value, market sales price and commercialization potential of non-cluster farming households in Ethiopia if they participate in cluster farming. Given that these clusters are still in their infancy, the findings lend support to the expansion of clusters, as they have the potential to increase smallholder commercialization. Fostering or expanding these clusters requires strengthening rural and community institutions, such as access to land, extension support, and financial services. Furthermore, strengthening the extension and outreach system will benefit smallholder farmers by reducing information asymmetry regarding knowledge and understanding of the existence and operation of cluster farming. Another line of our policy recommendation relates to the mounting evidence that smallholder commercialization increases welfare, food security, nutritional outcomes, and consumption levels, but little is said about where policy action can be taken to boost commercialization. Our findings suggest that the benefits of commercialization found in various studies can be sustained through cluster farming approaches.

In addition, given the disparities in commercialization benefits for households at different farm size classifications, agricultural development policies should consider heterogeneous household groups and resource levels when promoting cluster farming. For example, the government may encourage smallholders to produce with better input use by implementing necessary agronomic practices and promoting access to irrigation to increase productivity per unit area. Furthermore, through group action and an improved market information system, smallholders can be provided with marketing skills while also increasing their bargaining power. It is therefore indispensable to ensure that the poorest, household with a smaller landholding, groups of households also obtain the necessary benefits. Policy makers should also prioritize infrastructure improvements to improve connectivity between neighboring cluster farms to further promote interaction and learning, as well as ensure long-term mutual economic gains. It will be important for policy makers to also consider how to connect these cluster farms with other development programs, such as agro-industrial parks, which have the potential to create long-term market opportunities. In addition, integrating this cluster-based approach with environmentally-friendly and sustainable farm practices may be beneficial.

We end by pointing out some of the limitations of the study. First, while the ESR and IV models were used to deal with endogeneity arising from both observed and unobserved heterogeneities, the study used cross-sectional data, making it difficult to draw causal inferences. Although the pseudo-panel model alleviates some of this concern, it has its own limitations primarily due to possible information loss when constructing cohorts by grouping several households. Second, as context is always important, caution should be made when drawing generalizations from the analysis, especially given the unique type of cluster-based development approach in Ethiopia. Nonetheless, the study's findings could be used to provide learnings for developing countries where smallholder agriculture is the mainstay of economies. Notwithstanding, to our knowledge, this is one of the first attempts to study the role of cluster farming in smallholder commercialization. Follow-up studies are recommended to build on the findings of this study using panel data and improve the external validity of the study findings.

CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

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SUPPORTING INFORMATION

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APPENDIX A

Table A1a, TABLE A1b, Table A2, Table A3, Table A4, Table A5

TABLE A1a Instrument validity – relevance.

Variables	(1) Cluster farming
Neighborhood participation (dummy)	−0.03** (0.01)
Awareness of existence of agro-clusters (dummy)	0.29*** (0.01)
Storage facilities (dummy)	0.02** (0.01)
Extension access (dummy)	0.11*** (0.01)
Household size (number)	0.00* (0.00)
Age of head (years)	−0.00*** (0.00)
Primary education (dummy)	0.04*** (0.01)
Household head is female	0.11*** (0.02)
Year dummy	−0.04*** (0.01)
Group membership (dummy)	−0.02** (0.01)
Land holding (hectares)	−0.01*** (0.00)
Wheat dummy	0.02 (0.01)
Teff dummy	0.03** (0.02)
Malt barley dummy	0.02 (0.02)
Maize dummy	–
Tigray region	–
Oromia region	0.08*** (0.03)
Amhara region	0.02 (0.02)
Constant	−0.05* (0.02)
Observations	3969
R-squared	0.24

Note: Robust standard errors in parentheses ***$p < .01$, **$p < .05$, *$p < .1$.

TABLE A1b Joint-F test results – relevance.

Variable	R-square	Adjusted R-sq	Partial R-sq	$F(22,539)$	Prob >F
Cluster-farming (0–1)	00.29	0.29	0.12	232.18	0.00

TABLE A2 Test for overidentifying restrictions.

Score chi2(1)	0.553	($p = .457$)

TABLE A3 IV estimates of the effect of Cluster Farming on CI, MSV, and MSP.

	Commercialization index	Market surplus value	Market sale price
Cluster-Farming (0–1)	0.13**	389.45**	0.095
	(0.06)	(192.83)	(5.90)
Additional controls	Yes	Yes	Yes
Crop dummies	Yes	Yes	Yes
Region dummies	Yes	Yes	No
Time controls	Yes	Yes	Yes
Woreda fixed effects	Yes	Yes	Yes
R squared	0.03	0.00	.
Observations	3725	3969	3295

Note: Robust standard errors in parentheses ***$p < .01$, **$p < .05$, *$p < .1$.

TABLE A4 IV estimates of the effect of heterogeneity by farm size.

	Small land size (Cluster-farming)	Medium land size (Cluster-farming)	Large land size (Cluster-farming)
Commercialization index (CI)	0.04	0.30***	0.64***
	(0.10)	(0.08)	(0.23)
Market surplus value (MSV)	143.06	806.923***	3743.03***
	(108.31)	(297.05)	(1019.68)
Market sale price (MSP)	3.28	8.51*	16.90**
	(2.89)	(4.56)	(8.21)
Land size	≤ 1 ha	1 < ha <5	≥5 ha
Additional controls	Yes	Yes	Yes
Crop dummies	Yes	Yes	Yes
Region dummies	Yes	Yes	Yes
Time controls	Yes	Yes	Yes
Woreda fixed effects	Yes	No	Yes
Observations	043	2047	270

Note: Robust standard errors in parentheses ***$p < .01$, **$p < .05$, *$p < .1$.

TABLE A5 IV estimates of the effect of heterogeneity by crop cultivated.

	Maize	Wheat	Teff	Malt Barley	Sesame
Commercialization index (CI)	0.17*	−0.03	0.83***	0.38	−0.00
	(0.09)	(0.11)	(0.28)	(0.43)	(0.22)
Market surplus value (MSV)	339.65***	413.15	3457.46***	833.14	765.69**
	(110.49)	(313.82)	(1146.33)	(794.29)	(370.16)
Market sale price (MSP)	0.10	16.52***	19.49	−4.43	17.07
	(1.70)	(5.54)	(15.28)	(6.93)	(12.18)
Additional controls	Yes	Yes	Yes	Yes	Yes
Crop dummies	No	No	No	No	No
Region dummies	Yes	Yes	Yes	Yes	Yes
Time controls	Yes	Yes	Yes	Yes	Yes
Woreda fixed effects	Yes	No	No	No	Yes
Observations	1114	1092	511	499	251

Note: Robust standard errors in parentheses ***$p < .01$, **$p < .05$, *$p < .1$.