Agro-clusters, market imperfections, and technology adoption in Ethiopia: exploring impacts and pathways

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Abstract

Governments and development agencies in many developing countries have been promoting agro-cluster initiatives as a common avenue for promoting the adoption and diffusion of productivity-enhancing agricultural technologies. However, little is known about whether and under which conditions these agro-cluster schemes effectively promote the adoption of these inputs. Using a unique panel farm-household survey of about 5,000 smallholder farmers, we examine the impact of the agro-clusters on extensive and intensive adoption of agricultural technologies in Ethiopia. We employ a two-stage propensity score matching estimator using two broadly used matching algorithms, namely kernel and five-nearest neighbors matching methods. Our results suggest that the agro-cluster fosters both extensive and intensive adoption of modern agricultural inputs. We further undertake heterogeneity analysis to highlight the mechanism that enables agro-clusters to effectively promote the adoption of these inputs. The result shows that relaxing information and credit constraints may be the possible channels through which agro-clusters foster the adoption process. The findings also lend support to the widely held notion in development economics that households who are exposed to imperfect markets are unresponsive to government incentive schemes and opportunities to adopt new technologies. The findings provide strong evidence that the agro-cluster scheme may be a crucial policy instrument to promote the adoption of agricultural technologies with ensuing impacts on rural livelihoods and welfare.

Key Words: agro-clusters, agricultural technology, market imperfections, Ethiopia

JEL codes: C23, C24, D15, Q12, Q13

1. Introduction

Smallholder agriculture continues to characterize many developing economies, particularly in sub-Saharan Africa (FAO, 2010; Abay et al., 2018). However, the sector is entangled with subsistence farming and low productivity, limited technology adoption and diffusion, heavy reliance on erratic rainfall, high liquidity constraints, and other market imperfections (Deressa et al., 2009; Di Falco and Veronesi, 2013)**,** hence, the productivity growth remains stagnant (Liverpool-Tasie et al., 2017; Bold et al., 2017; Takahashi et al., 2019). Over the last few decades, modern agricultural inputs have been widely promoted as a pathway to improve the production and productivity of the sector and thus promote the welfare of the rural poor (Evenson and Gollin, 2003; Gollin, 2010; Holden & Westberg, 2016). Adoption and diffusion of innovative agricultural inputs are also emphasized as an important mechanism to facilitate the transition from subsistence agriculture to market-oriented agriculture in sub-Saharan African countries (De Janvry and Sadoulet, 2002; Mendola, 2007; Minten and Barrett, 2005; Zilberman et al., 2012; Bezu et al., 2014).

However, despite decades of efforts to promote the adoption and diffusion of these modern agricultural inputs, the adoption and rate of application of productivity-enhancing agricultural technology puzzlingly remain low (Janvry & Sadoulet, 2010; Abay et al., 2018; Sheahan and Barrett, 2017; Macours, 2019). A plethora of previous studies point out a variety of factors explaining low modern agricultural input uptake in low-income countries, including poor farmers' educational status (Asfaw & Admassie, 2004), limited access to credit (Croppenstedt et al., 2003; Gine & Klonner, 2008), poor access to information, high transaction costs, supply constraints, and other market imperfections (Abrar et al., 2004; Minten et al., 2013; Shiferaw et al., 2015). Moreover, studies also highlight that the adoption of modern agricultural inputs is hindered by the low soil quality and fertility status, land degradation and climate change-related shocks, especially among resource-constrained smallholder farmers in sub-Saharan Africa (Marenya and Barrett, 2009; Powlson et al., 2016; Wawire et al., 2021; Kanyenji et al., 2020).

There has recently been a resurgence of interest in rural institutions such as agro-clusters and other farm organizations, which use collective action to supplement government and private sector efforts to promote the uptake of new technology and practice (Shiferaw and Muricho, 2011; Manda et al., 2020; Joffre et al., 2019, 2020). A few pieces of literature highlight farm organizations in general and agro-clusters in particular increase interaction and cooperation among cluster farmers by building trust and fostering networks and partnerships between farmers and other supply chain actors. Using evidence from Zambia, Manda et al (2020) document that farm cooperatives increase the rate of agricultural technology adoption. Abeba and Haile et al (2012) highlight agricultural cooperative promotes the adoption of chemical fertilizer in Ethiopia. In the Philippines, vegetable agro-clusters have been shown to improve access to high-cost farm inputs (Montiflor et al., 2015). Joffre et al (2020) also show the positive role of agro-clusters in promoting the adoption of innovative agricultural technologies and practices in the aquaculture sector. Moreover, in recent studies, agro-clusters have been shown to increase smallholder commercialization with ensuing impacts on poverty reduction (Wardhana et al., 2017; Tabe-Ojong and Dureti, 2022).

In Ethiopia, agro-clusters have been part of a recent government policy initiative that targets specific geographical locations and different high-value and high-acreage crops throughout the country (Louhichi et al., 2019; ATA, 2019). The agro-cluster intervention in Ethiopia, called Agricultural Commercialization Clusters (ACC), aims to address the key challenges of scale and poor integration of smallholder farmers by increasing output and productivity while promoting and integrating commercialization activities (Louhichi et al., 2019; ATA, 2019). Specifically, agro-clusters are used as means to promote commercial opportunities for smallholder farmers by increasing the quantity and quality of agricultural inputs (e.g., chemical fertilizer, improved seed varieties, and agrochemicals) and facilitating market linkages in output markets (Louhichi et al., 2019; ATA, 2019; Tabe-Ojong and Dureti, 2022). Although the agro-cluster approach has been a key and popular policy aspect in Ethiopia since 2012, there is little evidence of its role, particularly in promoting the adoption and rate of application of innovative agricultural technologies.[1]

In this study, we examine the role of agro-clusters in relaxing structural constraints faced by most rural farm households and thus enhancing the adoption of modern agricultural technologies in Ethiopia. The study area provides an interesting context for two main reasons. First, the Ethiopian government's recent development efforts have been geared toward agro-clusters as a pathway to improve the production and productivity of the agricultural sector through increasing adoption and diffusion of productivity-enhancing agricultural technologies (Louhichi et al., 2019; ATA, 2019; Tabe-ojong and Dureti, 2022). Second, although modern agricultural inputs have been widely acknowledged as a pathway to improve productivity in Ethiopia, the intensification of these modern agricultural inputs such as improved seeds, chemical fertilizers, agrochemicals, and, others, remains low (Abay et al., 2017). Against this background, this study attempts to examine the role of agro-clusters in increasing the access to and rate of application of productivity-enhancing agricultural technologies such as improved seeds, chemical fertilizers, and agro-chemicals, using a multi-stage constrained approach.

The study uses two-wave panel data from a large-scale household survey with about 5000 observations. Relying on the strong hand of the government in the agro-cluster formation process, we employ a two-stage propensity score matching estimator to estimate the impact of agro-clusters on household extensive and intensive adoption of agricultural technologies. The matching procedure first accounts for the woreda-level characteristics and in the second step household-level characteristics. In the first step of matching, we use two key observable criteria (woreda level production potential and market access) that the government used to assign treatment to match woredas within agro-clusters with similar woredas outside the agro-cluster. In the second step, we match agro-cluster members with similar households living in woredas without an agro-cluster,

[1] Louhichi et al (2019) indicate that agro-clusters improved production and productivity in Ethiopia. Tabe-ojong and Dureti (2022) also highlight that agro-clusters in Ethiopia increase income and decrease poverty.

using a rich set of observable household characteristics and the score dummy from the first stage. In this way, we attempted to address potential sources of bias that can cause systematic differences between farm households located in agro-clusters and those that are not, thereby confounding the impact of agro-clusters on the outcome of interest.

2.1. Identification strategy

The comparability of the treatment group to the control group is critical for the credibility of any impact evaluation. If the control group systematically differs from the treatment group, any comparison of the outcome variables would reflect a combination of the true treatment effects and the impacts of these systematic differences between the two groups. As a result, the most credible estimation approach ensures that the treatment and control groups have identical distributions of observed and unobserved characteristics. The agro-cluster formation process involves three key steps. First, the government identifies strategic cluster crops at the national level based on the country's production potential and comparative advantage. Second, woredas with relatively higher production potential and market infrastructure were identified across the country[2]. Third, the agro-clusters were formed by grouping the neighboring selected woredas based on their geographic proximity and common priority crops[3] (ATA, 2019). Although the three steps highlight that the government has a strong hand in each step of agro-cluster formation, several potential factors drive a systematic difference between agro-cluster participants and their counterparts.

Based on this background, our empirical strategy aims to deal with these three potential sources of bias that can cause systematic differences between farm households located in agro-cluster and those that are not, confounding the impact of agro-clusters on the outcome of interest. First, since the initial selection is at the woreda level, farm households in agro-cluster and not in agro-cluster may not be comparable in terms of community-level observable characteristics that may have a direct effect on the outcome of interest such as market access and production potential. Second, farmers in agro-cluster may differ significantly from farmers not in agro-cluster farmers by a number of household-level observable characteristics (e.g., age, education, etc.), which may also have a direct influence on the outcome of interest. These two factors indicate that the observable differences between the two groups can be systematic, reflecting original differences rather than the effects of agro-cluster per se. Third, there may be unobservable household and community-level characteristics that contribute to the selection of woredas to be part of the agro-cluster in the given area in the first place. This can be the case, for example, if dynamic community leaders may play a role to influence the given woreda to be part of the cluster.

To deal with the first two sources of bias, we employ an identification strategy that relies on selection-on community-level and household-level observables. Specifically, our empirical approach involves a two-step matching estimator. First, we match woredas within agro-clusters

[2] This means woredas with higher production potential and market access are more likely to be part of the cluster.
[3] A cluster is formed by the selected woredas that share a border and grow the same priority crops. Once agro-clusters are established, all farm households in the clustered woredas are equally eligible for cluster intervention.

with similar woredas outside the agro-cluster using two key observable criteria (i.e. woreda level production potential and market access) that the government used to assign treatment[4]. In the second step, we match agro-cluster members with similar households living in woredas without an agro-cluster, given a rich set of observable household characteristics and score dummy from the first stage.

For the third source of bias, we assume that this particular source of bias does not pose a significant identification threat for the study at hand. This is because establishment of agro-cluster is exogenous to communities' unobservable characteristics as well as to that of their members. In other words, woredas are not self-selected into agro-clusters; rather, they are externally selected by the government in a top-down fashion based on their production potential and market access. Furthermore, the discussion with experts shows that the selection of woredas for the agro-cluster was determined based on the simulation model using woreda level data. Therefore, given the existence of an agro-cluster in a particular woreda is assumed to be independent of the decisions of its members, there is no reason to believe that the distribution of household-level unobservable characteristics differs systematically across woredas with similar observable characteristics. Consequently, we assume that differences in unobservable characteristics between members of agro-clusters and households with similar propensity scores (but living in woredas without agro-clusters) are random and will not bias the estimator.

3. Data, variable description, and matching

3.1 Household Survey

The study's empirical analysis is based on a national representative farm household survey conducted 2019 by Ethiopia Agricultural Transformation Agency (ATA) with technical and quality control support by the International Food Policy Research Institute (IFPRI). The survey area covered four main regions of Ethiopia (Amhara, Oromia, SNNPR, and Tigray) where agro-clusters have been promoted. In these regions, there are 30 ACC clusters in total, and the survey covered all agro-clusters with a representative household sample size. The sample of non-cluster households is designed to be representative of the non-cluster areas of these four regions and 30 clusters.

The objective of the surveys was to evaluate the ACC clusters performance by comparing cluster households with non-cluster households as well as comparing the cluster households themselves over time. To generate estimates of the key performance indicators, the sample was designed to contain at least 150 households per ACC cluster. To achieve this, the survey employed multi-stage stratified random sampling techniques. In the first stage, at least 5 woredas were randomly selected per each ACC cluster. From selected woredas, 2 kebeles were randomly selected. From selected

[4] We use the woreda-level greenness (vegetation) index to measure production potential for each woredas, and the road density index to measure market access.

kebeles, 15 farm households were interviewed. Whenever possible, replacement woredas and kebele were selected randomly to replace the inaccessible and insecure ones following the same sampling process. At the end, in total, about 5310 with 19% of control farm households were interviewed. These samples are drawn from 355 kebeles, 68 of which are outside clusters, and 154 woredas, 34 of which are outside clusters.[5]

3.1 Variable descriptions

In this study, we use three outcome variables as measures of technology adoption: improved seed, chemical fertilizer, and agro-chemicals. These outcome variables indicate whether and to what extent the farm household adopts specified agricultural technology. As shown in Table 2 below, chemical fertilizer indicate the volume of chemical fertilizer use per farming season. Improved seed and gro-chemical shows the amount of local currency the farm households spend on improved seed varieties and herbicides and pesticides each season, respectively.

Table 1: Summary statistics of the outcome variable

Variables	Control Mean	Treated Mean
Value of purchased seed (Birr)	130.8	681.7
Seed dummy (0/1)	0.234	0.423
Fertilizer total (kg)	37.84	115.3
Fertilizer dummy (0/1)	0.526	0.499
Value of pesticides & herbicides (Birr)	51.98	319.8
Pesticides & herbicides dummy (0/1)	0.217	0.412

Our data shows approximately 23.4% of farm households adopted improved seeds during both survey periods, the average size is 9.34 kg. The rate of fertilizer application is about 48% among farm households with an average size of 31.2 kg over the two periods. There is also an increase

[5] The interviews were carried out by a group of well-trained enumerators. The survey was designed and administered on survey-based tablets. The tablets were loaded with Survey CTO software and programmed to replicate the household, individual, kebele, and woreda questionnaires, which also enabled real-time quality checks and controls. The survey has a comprehensive household-level questionnaire, which captures information on both household socioeconomic characteristics and value chain activities. Specifically, it covered household socio-demographic characteristics (gender, age, education, and family size), household farm assets (land size, off-activities, total production, and market surplus output), use of crop inputs (seeds, fertilizer, agrochemical, mechanization) and social network (membership in self-help groups and cooperatives). Information was also captured on access to extension services, credit and savings, and gender.

from 2016 to 2019, both in terms of the number of households adopted and the average amount uptake. Regarding agro-chemicals, the adoption rate is about 22.6% of farm households, with an average uptake valued at 45.38 Birr.

3.2 Matching

Matching woredas

The first stage of our matching procedure entails the treatment woredas are sufficiently similar to the comparison ones. To do so, we use the notion of development domain, as adapted to Ethiopia by Chamberlin et al. (2006). Development domains are defined as geographic locations sharing broadly similar rural development constraints and opportunities (Bernard et al., 2008). The classification is based on the combination of four characteristics that best capture livelihood heterogeneity among smallholders in Ethiopia (Chamberlin et al., 2006; Bernard et al., 2008). These characteristics are altitude, population density, distance to the closest market, and moisture reliability. Although Chamberlin et al. (2006) use four characteristics, including population density, distance to the closest market, altitude, and moisture reliability, our classification is based on woreda production potential and market access as these two variables are key criteria that the government uses to assign treatment. We use the woreda-level greenness (vegetation) index to measure production potential for each woredas.

Table 3: First-stage matching summary statistics

Domains	Control woredas *Frequency* *(Percent)*	Treated woredas *Frequency* *(Percent)*
Low production potential, Low market access	3	9
	(9.091)	(7.563)
Low production potential, Medium market access	0	11
	(0.000)	(9.244)
Low production potential, High market access	7	18
	(21.21)	(15.13)
High production potential, Medium market access	2	20
	(6.061)	(16.81)
Medium production potential, Medium market access	2	12
	(6.061)	(10.08)
Medium production potential, High market access	3	10
	(9.091)	(8.403)
High production potential, Low market access	5	10
	(15.15)	(8.403)
Medium production potential, Low market access	4	16
	(12.12)	(13.45)
High production potential, High market access	7	13

	(21.21)	(10.92)
Total	33	119
	(100)	(100)

Note: "Low potential, Medium market access" group is dropped as there is no sufficient number of comparison wards.

Based on vegetation index and road density, we classify our sampled woredas into 9 mutually exclusive domains, as shown in table 1. The summary statistics in table 1 shows that a sufficient number of treatment and comparison woredas exist within each domain, except the domain with low production potential and medium market access. In our original sample, there are 154 woredas, 34 of which are outside the cluster. After dropping the 13 woredas (i.e. two woredas with missing observations and 11 woredas for which there is no sufficient number of comparison woredas), we ended up with 152 woredas, of which 119 agro-cluster woredas.

Matching households

Second-stage matching uses the subsample of households from the first-stage to conduct household level matching. The sub-sample now contains 4,476 households with 930 in comparison woredas and 3,549 treated households in the treatment woredas. We employ canonical probit regression to generate propensity scores given rich set of farm household characteristics. The propensity score $P(X)$ is defined as the conditional probability of receiving a treatment given household characteristics as:

$$P(X) = E(X) = prob\,(D_i = |X)$$

where X refers to a vector of household characteristics. The household characteristics included in the estimation of the propensity score such as household size, sex, age, education, off-farm income, livestock size (TLU), plot size, distance to the nearest road, distance to the nearest market, distance to nearest agricultural input dealer, and distance to the nearest farmer training center. Domain dummies are used to ensure that the households matching is conditional on domain. Figure. 1 depicts the distribution of propensity scores for both the treatment and comparison groups. The figure indicates that the distributions are fairly similar, implying that estimated average treatment effect is expected to be not sensitive to the use of different matching algorithms.

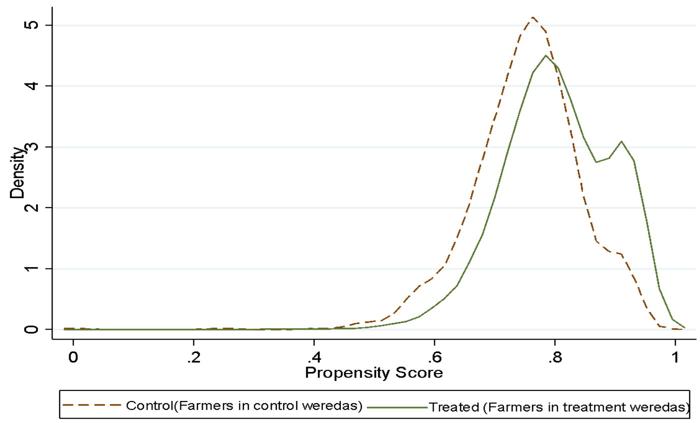

Fig. 1. Propensity scores distribution among treatment and control groups

Various matching methods can be used to match 3,549 treated households with their non-agro-cluster participants based on estimated propensity score. Here we focus on two broadly used matching algorithms, namely kernel matching method proposed by Heckman et al. (1998), and five-nearest neighbors matching. Kernel matching method that links the outcome of the treated household with a matched outcome calculated as the kernel-weighted average of all the non-treated households (Ali and Peerlings, 2012). Using the weighted average of all non-treated households to construct the counterfactual outcome results in kernel matching having a lower variance advantage due to the utilization of more information (Heckman et al., 1997, 1998). A kernel function can take different forms, and in this study, the *Epanechinikov* kernel functional form is used for the matching results reported in Table 7.

The k-nearest-neighbors matching, on the other hand, is used to match each agro-cluster participant with k comparable non-participants, where comparability is measured in terms of distance to the nearest propensity score (Cunningham, 2021). In order to increase comparability between the treatment and comparison groups, the sample has been limited to the common support region. This region is defined as the range of propensity score values where both treatment and comparison observations are present.

Table 4: the indicators of matching quality of the kernel matching and 5-nearest-neighbors matching

Methods	P-value (unmatched)	P-value (matched)	Mean bias (unmatched)	Mean bias (matched)	Bias reduction
Kernel	0.000	0.243	8.3	2.1	
Five-NN	0.000	0.162	8.3	2.4	

Note: P-value of likelihood ratio test ($Prob > \chi 2$). Bias (in percentage) is calculated as the difference of sample mean of outcome variable of the treated and non-treated groups times the square root of the average of the sample variance of outcome variable of the treated and non-treated groups (Rosenbaum and Rubin, 1985).

To ensure that households with a similar probability of being agro-cluster have the same distribution of pre-exposure characteristics, we performed a balancing hypothesis test of covariates. Table 4 presents the indicators of matching quality of each matching algorithm at hand. Columns II and III display the outcomes of the chi-square test for the joint significance of covariates used in the probit model before and after the match (Sianesi, 2004). The chi-square test following the kernel match demonstrates that none of the covariates in the probit model are jointly significant with $prob > \chi^2 = 0.243$ for all outcomes of interest. For the exit decision model, the chi-square tests after the match in column II indicate that the covariates of the probit model are not jointly significant with $prob > \chi^2 = 0.162$ for all three measures of household well-being.

Another measure employed to evaluate the match's quality is the mean bias reduction after the match (Rosenbaum and Rubin, 1985), as shown in column last Column of table 4. The bias reduction of covariates after the kernel match lies well below the suggested 20% level of bias by Rosenbaum and Rubin (1985). The matching quality tests statistics for 5-nearest neighbor matching are fairly similar to kernel matching test statistics. Overall, the matching quality tests statistics demonstrate that the matching algorithms at hand have performed well in avoiding systematic differences in the distribution of observable covariates between the agro-cluster participants and their counterparts.

4 Results and discussion

4.1 Probability of adoption of agricultural technology

We first estimate the effects of agro-clusters on the likelihood of adopting chemical fertilizers, improved seeds, and agro-chemicals after matching community and household characteristics. Table 5 displays the nonparametric estimates of the average treatment effect on the treated (ATT) of the association between agro-clusters and the likelihood of adopting these agricultural inputs. The result shows that membership in an agro-cluster is associated with a higher likelihood of adopting agricultural inputs. Looking at the Kernel-based matching estimates, on average, membership in agro-clusters increases the probability of chemical fertilizers, improved seeds, and agro-chemicals use by roughly 13%, 7.8%, and 11.2%, respectively, compared to the non-member counterparts. The estimated coefficients also have similar signs and close magnitudes for both Kernel-based matching and Nearest-neighbor matching.

Table 5: Impact of agro-cluster on the probability of adoption of agricultural technology

	Kernel based matching			Nearest-neighbor matching		
	Fertilizer	Improved seeds	Agrochemicals	Fertilizer	Improved seeds	Agrochemicals
ATT	0.127***	0.0775***	0.112***	0.144***	0.0595**	0.117***
	(0.0171)	(0.0185)	(0.0181)	(0.0239)	(0.0288)	(0.0236)
Obs.: off support	33	33	33	33	33	33
Obs.: on support	4,445	4,445	4,445	4,445	4,445	4,445

Note: Standard errors in parenthesis are computed after bootstrapping 50 times. ***, ** and * refer to significance at 1%, 5% and 10% respectively.

4.2 The intensity of agricultural technology use

In the second stage, we estimate the association of agro-clusters and intensive adoption of fertilizers, improved seeds, and agro-chemicals use. Table 6 presents the ATT estimates after matching community and household level characteristics of agro-cluster members and non-members. Again, the overall results show that agro-clusters increase the intensive adoption of these agricultural inputs. The result is consistent in sign and magnitudes for both matching methods. As shown in Table 6, the kernel based matching estimates show that membership in an agro-cluster increases the uptake of chemical fertilizers by roughly 68 kilo-grams, holding other factors constant. The agro-cluster participation also significantly increases the purchase of improved seeds and agro-chemicals by 190 and 104 ETB[6], respectively.

Table 6: Impact of agro-cluster on the intensity of adoption of modern agricultural inputs

	Kernel matching			Nearest-neighbor matching		
	Fertilizer	Improved seeds	Agrochemicals	Fertilizer	Improved seeds	Agrochemicals
ATT	67.94***	190.0*	104.1***	74.76***	202.9**	103.1***
	(10.59)	(103.6)	(20.51)	(11.34)	(85.17)	(20.18)
Obs.: off support	33	33	33	33	33	33
Obs.: on support	4,445	4,445	4,445	4,445	4,445	4,445

Note: Standard errors in parenthesis are computed after bootstrapping 50 times. ***, ** and * refer to significance at 1%, 5% and 10% respectively.

The overall findings are statistically significant indicating the importance of agro-clusters in establishing networks, dissemination information and improving economies of scale for smallholder farmers and thereby promoting extensive and intensive use of both productivity-enhancing and loss- reducing agricultural technologies. The findings also suggest that agro-clusters promotion can play a significant role in the government's endeavor to improve welfare of rural poor in particular and to achieve agriculture-lead industrialization in general through promoting extensive and intensive use of modern agricultural inputs.

4.3 Heterogeneous effects of agro-cluster participation based on underlying constraints

Although agro-clusters appear to improve agri-cultural input adoption, the mechanism by which this occurs is not clear. In this section, we attempt to highlight the mechanism that enables agro-clusters to effectively promote the adoption of these agri-cultural inputs. In the first place, farmers must be aware of the potential benefits and associated costs of the agri-cultural technology if they

[6] ETB (Birr) is the unit of currency in Ethiopia. 1 USD = 53.792242 ETB Feb 27, 2023.

are to test and determine its performance relative to other conventional technologies (Shiferaw et al. 2015). In the absence of such information, the farmer will not have the opportunity to adopt the new technology (Shiferaw et al. 2015). Given this, improving access to information is one of potential channels through which agro-clusters could influence the pervasive and intensive adoption of these innovative agricultural technologies. Similarly, as widely documented in early literature, modern agricultural innovations require adequate financial well-being in order to be effectively adopted. Hence, we hypothesized that agro-clusters could also alleviate the liquidity constraints of farm households that seem to find it difficult to afford these high-cost agricultural technologies. Based on this, we tested access to information and credit as two possible channels through which agro-clusters can enable the adoption of agricultural inputs. For this, we conducted a heterogeneity analysis of households with no access to both extension information and credit facilities versus households with access to at least one of the two, as shown in Table 7.

Table 7: Heterogeneous effects of membership on technology adoption

	No access to credit and info.			Have access to at least credit or info.		
	Fertilizer	Improved seeds	Agrochemicals	Fertilizer	Improved seeds	Agrochemicals
Panel a: Probability of adoption						
ATT	0.130***	0.101**	0.120***	0.140***	0.0670*	0.140***
	(0.0298)	(0.0407)	(0.0276)	(0.0376)	(0.0366)	(0.0278)
N	1509	1509	1509	2970	2970	2970
Panel b: Intensity of adoption						
ATT	55.60***	277.3**	97.35***	81.24***	79.62	123.0***
	(9.875)	(109.2)	(17.64)	(15.96)	(140.1)	(28.01)
Obs.: off support	13	13	13	13	13	13
Obs.: on support	1,496	1,496	1,496	1,496	1,496	1,496

Note: Standard errors in parenthesis are computed after bootstrapping 50 times. ***, ** and * refer to significance at 1%, 5% and 10% respectively.

5 Conclusion

Collective action schemes such as agro-clusters often aim at fostering agricultural productivity with ensuing impacts on sustainability and welfare. However, little is known about whether and under which conditions these schemes effectively promote the adoption of productivity-enhancing agricultural technologies and thus the welfare of the rural poor. Relying on the strong hand of government in agro-cluster formation process, we employ a two-stage propensity score matching estimator to estimate the impact of agro-clusters on household extensive and intensive adoption of agricultural technologies. First, we use two key observable criteria (woreda level production potential and market access) that the government used to assign treatment to match woredas within agro-clusters with similar woredas outside the agro-cluster. In the second step, we match agro-cluster members with similar households living in woredas without an agro-cluster, using a rich set of observable household characteristics and the score dummy from the first stage. In this way, we attempted to address potential sources of bias that can cause systematic differences between farm households located in agro-clusters and those that are not, as well as confounding the impact of agro-clusters on the outcome of interest.

Our findings show that agro-clusters positively and significantly affect both access to information and access to credit facilities. The results imply that agro-clusters play a positive role in promoting farm households' network and interaction within clusters, as well as strengthened ties with government and private institutions, allowing for better access to information and credit. In the second and third models, we assess the impact of agro-clusters on the probability and intensity of farm household technology adoption. Our results reveal that agro-clusters, in general, foster both adoption and intensity of modern agricultural input use. However, the effect appears to be more pronounced for the households that have been less exposed to credit and information constraints. This implies that easing information and credit constraints are the possible channel through which the agro-clusters scheme fosters both the probability and intensity of the adoption of innovative agricultural inputs. These results are also robust to different models and specifications including Augmented Inverse Propensity Weighted Regression (AIPWR) and alternative conventional technology measures like manure.

The empirical analysis in this article provides several interesting findings including some relevant policy implications. First, the significant contribution of agro-clusters to improving farm household adoption of modern technologies should motivate policy makers to strengthen their efforts to roll out the approach to different parts of the country. Our findings show that agro-clusters not only increase the probability of this technology adoption but also help to relax the institutional constraints such as extension information and formal credit. Therefore, fostering or expanding these agro-clusters requires strengthening rural and community institutions, such as access to land, extension support, and financial services to make agro-clusters more effective policy instruments. 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 agro-clusters, thereby increasing their effective participation and increased use of modern agricultural technologies. However, given that these agro-clusters are still in their infancy, the findings may lend support to the further expansion of agro-clusters, as they have the potential to promote technology adoption. The study's findings can also be used by policymakers and experts to scale up existing initiatives or propose new interventions aimed at facilitating the wider adoption of modern technology and best practices in developing countries.

Another line of our policy recommendation relates to the mounting evidence that modern technologies increase welfare, food security, nutritional outcomes, and consumption levels, but little is said about where policy action can be taken to boost the adoption of these technologies. Our findings suggest that the benefits of these technologies as found in various studies can be scaled up and sustained through agro-clusters. In addition, agricultural development policies should also consider heterogeneous household groups and resource levels when promoting existing or new agro-clusters to ensure that the poorest, least developed, group of households also obtain necessary benefits. Policymakers should also prioritize infrastructure improvements to improve connectivity between neighboring agro-clusters to further promote interaction and learning, as well as ensure long-term mutual economic gains. It will be important for policy 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 and welfare improvements.

The study has also some limitations. First, although we used panel data evidence and dealt with both observed and unobserved heterogeneities, we are still hesitant to call our findings causal inferences. This is due in part to the binary nature of our treatment variable, the agro-cluster. Given this, we were unable to use a more appropriate and practical fixed effect estimation strategy, which would have resulted in an incidental problem. Second, as context is always important, caution should be made when drawing generalizations from the analysis. Nonetheless, the study's findings could be generalized to developing countries' contexts since the situation in Ethiopia may be similar to that of other countries where agriculture is typically the mainstay of the economy. Notwithstanding, to our knowledge, this is one of the first attempts to study the role of agro-clusters to improve the adoption of agricultural technologies at the household level. Follow-up studies are recommended to build on this and improve the external validity of the study findings.

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