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ORIGINAL ARTICLE

Are agro-clusters pro-poor? Evidence from Ethiopia

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Abstract

Governments and development agencies increasingly promote agro-clusters as a pathway to improving smallholder incomes and ensuring inclusive rural development through mitigating production and market risks. However, there is very limited empirical evidence to support this promise. We use a large farm household survey of about 4000 smallholder farmers in Ethiopia growing cereals like teff, maize, wheat, maltbarley and sesame to examine the relationship between agro-clusters and smallholder welfare and poverty. Using instrumental variable estimators, we establish a positive association between agro-clusters, household income and per capita income. Agro-clusters are also shown to reduce poverty and poverty gaps. Our results are robust over different agro-cluster proxies and alternative estimators, such as the augmented inverse probability weighting estimator. We also show that our findings are unlikely to be driven by omitted variable bias. Moving beyond average effects and in the interest of understanding heterogeneous effects, we use quantile regressions at different income levels. We find that agro-clusters are associated with welfare gains for all households. However, the most significant gains are observed for the wealthier households. Despite this regressive association, our findings suggest that agro-clusters may be useful in making farming more profitable with significant welfare implications.

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KEYWORDS

agro-clusters, Ethiopia, poverty, welfare

JEL CLASSIFICATION

C21; I32; Q12; Q13

1 | INTRODUCTION

Poverty is a persistent problem in many parts of the world, especially in sub-Saharan Africa (SSA), where chronic poverty remains high, despite some pro-poor growth spurts in the region¹ (Dang & Dabalen, 2019). Poverty is exceptionally high in rural areas, where development is challenging (Mwabu & Thorbecke, 2004). The vast majority of people (approximately 82%) in SSA live in these rural areas and are mainly employed in agriculture, which remains their primary source of livelihoods (Dercon & Gollin, 2014). To promote economic growth and development in rural areas and achieve shared prosperity, many governments and development agencies have emphasised agriculture as a necessary pathway out of poverty (Barrett et al., 2019).

Governments and development agencies increasingly promote agro-clusters as a pathway to increasing smallholder incomes and ensuring inclusive rural development through mitigating production and market risks (Dirven, 1999; Wardhana et al., 2017). Agro-clusters are defined as a concentration of agricultural activities creating income and employment opportunities in and around a particular region (Galvez-Nogales & Webber, 2017). They can be effective in linking smallholder farmers to emerging food value chains and markets, with significant welfare implications (Burger, 1999; Poulton et al., 2010). Agro-clusters could make smallholder farmers productive, competitive and more generally attain economies of scale. Furthermore, clusters could lead to sustainable rural development through their effects on communities' economic, socio-cultural and environmental activities (Brasier et al., 2007).

Beyond such community-level effects, agro-clusters can stimulate technology adoption (Joffre et al., 2019, 2020), and because they increase the use of improved production practices, they may also affect agricultural productivity (Wardhana et al., 2017). The extant literature highlights increased interaction and cooperation as building trust and leading to the impacts of agro-clusters (Joffre et al., 2019, 2020; Wardhana et al., 2020). These clusters are usually characterised by mutual social and economic interactions between farmers, which help achieve production and commercialisation goals, and improve linkages with development agencies, research institutions and government. These clusters could also improve smallholder welfare and reduce poverty by increasing income and generating employment. However, empirical evidence of these effects is presently limited.

We examine the relationship between agro-clusters, welfare improvements, and rural poverty in Ethiopia. Ethiopia is an interesting case study because the government is using agro-clusters as vehicles for reducing poverty and stimulating rural development. Our analysis is based on a farm household survey of about 4000 households growing cereals (maize, wheat, teff, maltbarley, and sesame) which are priority crops for the clusters and the country's main staple crops. We use ordinary least squares (OLS) and instrumental variable (IV) estimators to estimate the association between the share of allocated land to a cluster with household income, per capita income, poverty and poverty gaps. To the best of our knowledge, this is the first study to examine the relationship between agro-clusters and poverty from a smallholder

¹This growth was accompanied by a 9% reduction in poverty and a growing middle class. About 60% of the poor in Africa are chronically poor, and 40% are in transient poverty.

farm household perspective. Wardhana et al. (2017) look at agro-clusters but only assess the effects on poverty rates at a district level, looking closely at spillover and neighbouring spatial effects. This analysis builds more on their aggregated results.

The rest of the article is structured as follows. Section 2 describes the concept of agro-clusters in the Ethiopian context. The farm household survey data and variable definitions are presented in Section 3, and Section 4 presents the estimation strategy. The results are presented and discussed in Section 5. Policy implications from the study are discussed in Section 6 and Section 7 concludes.

2 | THE CONCEPT OF AGRO-CLUSTERS

Although extant literature has used the cluster concept for about two decades, the term has no clear definition as different actors (policy-makers, institutions and economic sectors) use it in different contexts and intentions (Galvez-Nogales & Webber, 2017; Steffens, 2016). One of the most commonly used definitions is a geographic concentration of interconnected firms and institutions (Porter, 1998). The other related definition is 'an agglomeration or production network' where geographical proximity favours economies of scale, interactions between different actors, and information flows and access to markets (Galvez-Nogales & Webber, 2017; Wardhana et al., 2017). In the context of the agricultural sector, agro-cluster is the preferred term, defined as the concentration of agricultural activities creating income and employment opportunities in and around a particular region (Galvez-Nogales & Webber, 2017).

According to Galvez-Nogales (2010), agro-clusters are characterised by three pillars of interaction between the actors involved: horizontal, vertical and supportive. Horizontal interaction is a reciprocal relationship between farmers or other actors at a particular value chain level; these relationships allow value chain agents to reduce competition among themselves and improve their bargaining position in the market. The vertical pillar is an interaction along the value chain, such as agricultural production, food processing and food marketing, and is about improving product flows and adding value. The supportive linkage involves agents such as research institutions, universities and governments. Based on the combination of these interactions, agro-clusters could create synergies, enabling small-scale producers to become more competitive, overcome the constraints of poor access to services (including inputs and information), share the costs of adopting technologies and practices, and mitigate various sources of risks (Galvez-Nogales, 2010).

Many developing countries, especially in Asia, have shown significant success with agro-clusters (Minten et al., 2020). Zhang and Hu (2014) show the success of a potato agro-cluster in boosting potato production and fostering rural development in China. In the Philippines, vegetable agro-clusters have been shown to improve access to farm inputs and increase market surplus (Montiflor et al., 2015). Agro-clusters have also been shown to reduce poverty in Indonesia, highlighting the role of localisation externalities in encouraging agricultural transformation (Wardhana et al., 2017, 2020). Examining agricultural and food industry clusters in the United States, Goetz et al. (2004) highlight the profitability and productivity implications of clusters. They further argue that clusters provide smallholder farmers with countervailing market power and offer regions a source of competitive advantage. Beyond staple and vegetable crops, agro-clusters have also been used in the aquaculture sector. In Fiji, agro-clusters have been shown to be instrumental in increasing fish production, enabling farmers to enjoy the benefits accruing to economies of scale (Varawa et al., 2014). Using the case of shrimp farming in the Mekong Delta region of Vietnam, Joffre et al. (2020) examine the participation of small-scale aquaculture farmers in production clusters. They show that clustering is a promising avenue for fostering interactions among farmers, and inducing the adoption of better aquaculture practices.

In Ethiopia, agriculture still plays a crucial role contributing to 33% of GDP, 83.9% of exports and 84% of employment (National Bank of Ethiopia, 2019). However, the sector is still largely subsistence-based, plagued with low productivity, outdated technologies, inadequate infrastructure and institutions, and depending on erratic rainfall, inter alia (CSA, 2020). In the last decades, the country has embarked on several initiatives to address these challenges and improve smallholder welfare and reduce the poverty quagmire (Tabe-Ojong et al., 2021, 2022). In its most recent development efforts, the country introduced Agricultural Commercialisation Clusters (hereafter ACC) as the main approach to enhance smallholder livelihoods and drive rural industrialisation (ATA, 2019; Louhichi et al., 2019). ACC is a policy intervention that targets specific geographic locations and some priority crops across the country (ATA, 2019; Louhichi et al., 2019). The approach addresses the key challenges of scale and poor integration of smallholder farmers by improving production and productivity while promoting and integrating commercialisation activities (ATA, 2019; Louhichi et al., 2019).

Within the ACC approach, a more specific intervention was introduced called Farmer Production Clusters (FPC), where smallholder farmers with adjacent farm plots voluntarily pool a portion of their land to benefit from targeted government support for selected crop value chains and cluster economic agglomeration (ATA, 2019). Smallholders participating in the same FPC are expected to cooperate by producing similar crops and benefit from associated incentive packages including the provision of basic inputs (e.g., fertilisers, improved seeds, credit, mechanisation, etc.), storage and transport facilities, and market linkages (e.g., contract farming) (ATA, 2019). Moreover, smallholder farmers benefit from cluster economies of scale such as greater affordability of modern technology (e.g., sharing the overhead costs of tractors), stronger bargaining power (e.g., negotiating favourable prices for their products), stronger market linkages to serve bulk buyers or large-scale buyers (e.g., contract farming with large processors), and faster dissemination of best practices and extension services among farmers (ATA, 2019).

3 | DATA COLLECTION AND VARIABLE MEASUREMENT

3.1 | Farm household survey

We use a farm household survey of smallholder households across four main regions in Ethiopia: Amhara, Oromia, Southern Nations, Nationalities and Peoples' Region (SNNPR), and Tigray. A total of about 4000 households were interviewed over two consecutive periods in 2019 and 2020, as part of the assessment of the performance of agro-clusters. A multistage sampling technique was used to select households in the two survey 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 with the control woredas being woredas where cluster farming does not exist at the time of the survey. These control woredas are similar to the treatment woredas except for the fact that the clustering approach has not been promoted and does not exist in them. The treatment and control woredas have similar farming systems, cultivate similar crops and belong to similar agro-ecological zones. 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 there.² From these 75 woredas, kebeles were randomly selected and households were further randomly selected for interviews. Given that households were randomly selected even in the treatment woredas, we interviewed both households that belong to

²Our data confirms this as we do not record any participation in agro-clusters from the control woredas.

agro-clusters and those that do not. About 25% of households did not participate in agro-clusters in the treatment woredas.

This sampling strategy has the advantage of significantly reducing selection bias within each woreda (Ruml & Qaim, 2021). Although our treatment and control woredas are similar, we control for woreda fixed effects in the regressions as part of our empirical strategy. Beyond woreda differences, we further address the issue of self-selection bias below.

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 supervised 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-farm activities, total production and market surplus output), and social network (neighbour participation in agro-clusters, awareness and membership in self-help groups). Information was also captured on access to extension services and credit.

Although we have a two-period data, these data cannot be treated as a panel as 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 reached 3978 households over the 2 years, but due to some missing entries, we only used 3969 households in the analysis.

3.2 | Measuring outcome variables

Four outcome variables are proxies for smallholder welfare and poverty; household income, per capita income, income poverty and income poverty gap. Income was measured in ETB³ annually, adjusted for inflation using consumer price indices; it was converted to USD purchasing power parity using the 2017 International Comparison Program conversion rates. Per capita income was used to understand and evaluate the standard of living and quality of life of sampled households.

For income poverty, the international poverty line of US\$1.90 a day was used as a baseline to compare with household per capita income. Households with a per capita income above this line were given a zero value, while households below were given a value of one. Similarly, the income poverty gap was calculated by subtracting the per capita income of households from the international poverty line, divided by the poverty line. Some households had per capita incomes above the poverty line, which led to some negative gaps; thus, zeros were assigned to these households. Calculating the poverty gap this way constrains the values between zero and one, enabling comparison.

3.3 | Measuring agro-clusters

Participation in agro-clusters was measured using three different proxies. First, participation was measured as a dummy, which takes the value of one for households that belong to agro-clusters and zero otherwise. Participation in agro-clusters require households to offer a minimum of 0.25 hectares of land and grow some key crops. Thus, every farmer's land contribution is used as a second measure of agro-cluster participation.

³ETB stands for Ethiopian birr, which is the Ethiopian currency.

Using the amount of land allocated to a cluster makes comparison between households not possible. As the amount depends on the total landholding, we use the share of total land contributed.

4 | ESTIMATION STRATEGY

Given that we have cross-sectional data, we estimate the following regression model:

$$Y_i = \beta_0 + \delta C_i + \gamma' X_i + \varepsilon_i, \quad (1)$$

where Y_i is the welfare and poverty indicator for household i , C_i is the share of land allocated to the cluster by the household, X_i is a vector of control variables, and ε_i is the stochastic error term. Two different models are estimated for each outcome variable; we control for various farm household characteristics associated with rural poverty through channels other than participating in agro-clusters. We use the OLS estimator for all the continuous dependent variables. For income poverty, which is a dummy, we also use a linear probability model, which usually avoids identification by functional form common in logit and probit models.

The main parameter of interest from Equation (1) is δ , which indicates the relationship between agro-clusters and rural poverty. We hypothesize a positive relationship between agro-clusters and income measures, and a negative relationship with poverty and poverty gap; the parameter estimate should be positive for income indicators and negative for poverty outcomes. Assuming strict exogeneity, the OLS estimations should provide unbiased estimates of the relationship between agro-clusters and rural poverty. However, strict exogeneity does not reflect reality, and the share of land allocated to a cluster may be potentially endogenous. Endogeneity of agro-clusters may arise from measurement error, reverse causality and unobserved heterogeneity.

In the case of measurement error, it is always challenging to claim the accuracy of the data generating process. Still, we are certain that cluster participation was well captured with the actual amount of land allocated by farmers, given that these processes were well supervised and monitored. Before joining the clusters, the actual amount of land contributed by farmers to the clusters was measured using GPS techniques. For unobserved heterogeneity, it is possible that unobserved factors, such as risks, preferences and managerial abilities, may drive the amount of land that households allocate to clusters and be correlated with poverty. As we only use cross-sectional data, it is difficult to satisfactorily control for this eventuality beyond including different controls and observing the stability of the coefficients. Additionally, we follow Oster (2019) to evaluate the robustness of the estimated coefficients to omitted variable bias.

Finally, there could be reverse causality issues between agro-clusters and the welfare and poverty indicators. Allocating more land to clusters may increase income and reduce poverty through the associated benefits of pooling resources from other households and enjoying economies of scale when it comes to input purchases and commercialisation. Households that are generally more advantaged in income may allocate more land than their peers. But can increase in income lead to land expansion? This relationship may only hold for households who allocate only small shares of their landholdings. There may be little or no income–land allocation effect for households that allocate most or all of their lands to the cluster limiting threats of reverse causality.

Nevertheless, we employ IV estimators to control for any residual endogeneity especially given non-random self-selection into agro-clusters in the treatment wordedas. We specify two instruments: awareness of the existence of agro-clusters and neighbour participation in

agro-clusters. These instruments are motivated by the premise that networks ease information flow and reduce the barriers facing farmers in rural areas (Di Falco et al., 2020).

Given that agro-clusters are a new concept in the study area, awareness of their existence and functioning are necessary pre-conditions to participation. Awareness of agro-clusters is significantly correlated and positively determines participation in agro-clusters ($R^2 = 26\%$, $p = 0.00$). Neighbourhood participation is also positively related to participation in agro-clusters ($R^2 = 26\%$, $p = 0.06$). These two findings already validate the instruments based on the relevance condition (full results are provided in the [Appendix S1](#)).

Examining the second condition of instrument exogeneity requires verifying if the instruments directly affect poverty; intuitively, no effects are anticipated, except through agro-clusters. Being aware of an agro-cluster or knowing if a peer is participating in these clusters, seemingly does not affect our outcomes. Apart from conceptually motivating this condition, there is typically no statistical test for this. However, because this study has two instruments, Wooldridge's score test of over-identifying restrictions, which is heteroscedasticity-robust is conducted⁴ (Wooldridge, 1995). As shown in the [Appendix S1](#), statistically insignificant estimates are obtained. Thus, we fail to reject the null hypothesis that the instruments are valid.

4.1 | Effect heterogeneity

Given that the effects of agro-clusters may have a heterogeneous association with household welfare and rural poverty, we further examine this heterogeneity and establish which group of households benefit most using quantile regressions. Using the same connotations as in [Equation \(1\)](#) above, we estimate the following regression model:

$$Y_i = X_i' \partial_\varphi + \varepsilon_i, (y_i | X_i) = X_i' \partial_i \quad (2)$$

X_i is a vector of explanatory variables, including agro-clusters. $(Y_i | X_i)$ is the conditional quantile of Y_i at quantile φ . We estimate the association between agro-clusters and rural poverty using nine different quantiles ($\partial_\varphi = 0.10, 0.20, 0.30, 0.40, 0.50, 0.60, 0.70, 0.80$ and 0.90). $\partial_\varphi = 0.10$ represents the poorest group of households.

5 | RESULTS AND DISCUSSION

5.1 | Characterising the sample

[Table 1](#) presents the summary statistics of the outcome variables and the explanatory variables used in the regression framework. Households in the study area report an annual income of US\$1340, which falls to US\$235 when viewed per capita. Approximately 60% of the households can be termed poor based on the US\$1.90 international poverty line, with an associated income poverty gap of 35%.

Regarding participation in agro-clusters, about 57% of households in the study area belong to agro-clusters, where they allocate an average of 0.60 hectares of land to the clusters. Regarding their total landholdings, which are about 2.25 hectares, households allocate a share of 0.27 to the cluster. There are about 17 members per cluster, and the total land per cluster is approximately 12 hectares. Most household heads are middle-aged, averaging about 43 years

⁴Though not an instrument exogeneity test, an over-identification test provides statistical validation that additional instruments are exogenous.

TABLE 1 Summary statistics

	Mean	Std. dev.
Outcome variables		
Income (US\$)	1340.94	2724.22
Per capita income (US\$)	235.40	576.91
Income poverty (dummy)	0.61	0.48
Income poverty gap (0–1)	0.35	0.35
Variables of interest		
Agro-clusters (dummy)	0.57	0.49
Plot allocated to cluster (hectares)	0.60	0.87
Agro-clusters (0–1)	0.27	0.31
Other control variables		
Total cluster size (hectares)	11.46	16.88
Cluster size (number)	16.63	24.56
Age of household head (years)	42.67	11.02
Primary education (dummy)	0.73	0.44
Household head is female (dummy)	0.09	0.29
Household size (number)	6.51	2.44
Landholding (hectares)	2.25	1.96
Group membership (dummy)	0.37	0.48
Credit access (dummy)	0.29	0.45
Extension access (dummy)	0.90	0.29
Storage facilities (dummy)	0.59	0.49
Off-farm income (dummy)	0.40	0.49
Wheat (dummy)	0.29	0.45
Teff (dummy)	0.14	0.34
Sesame (dummy)	0.07	0.26
Maltbarley (dummy)	0.14	0.34
Maize (dummy)	0.34	0.47
Neighbourhood participation (dummy)	0.22	0.42
Awareness of agro-clusters (dummy)	0.78	0.41
Observations	3969	3969

of age. Households are mostly male headed, with a household size of about seven members. Extension access in the study area is widespread (90%), and 73% of household heads have achieved primary education.

Significant differences are observed between households based on income and poverty outcomes (Table 2). Specifically, households in agro-clusters have higher household and per capita incomes than their non-participating counterparts. Similarly, such households appear less impoverished under both income poverty and income poverty gap measures. Households in clusters generally have more land, and their heads are younger than their peers who do not belong to agro-clusters. Although these results offer some interesting insights, they do not control for potential confoundings.

TABLE 2 Mean differences based on participation in agro-clusters

	Participants	Non-participants	t-test
Income (US\$)	1668.93 (71.57)	905.87 (30.24)	***
Per capita income (US\$)	293.64 (15.40)	158.15 (5.48)	***
Income poverty (dummy)	0.55 (0.01)	0.69 (0.01)	***
Income poverty gap (0–1)	0.30 (0.07)	0.42 (0.08)	***
Land holding (hectares)	2.54 (0.04)	1.87 (0.03)	***
Household size (number)	6.64 (0.05)	6.33 (0.05)	***
Age of household head (years)	41.98 (0.21)	43.59 (0.28)	***
Observations	2263	1706	

Notes: Robust standard errors are in parentheses.

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

TABLE 3 Effect of agro-clusters on income and per capita income

	Income		Per capita income	
	OLS	IV	OLS	IV
Agro-clusters (0–1)	1332.26*** (446.21)	1038.14*** (414.63)	262.58*** (89.73)	164.36*** (72.45)
Additional controls	Yes	Yes	Yes	Yes
Crop dummies	Yes	Yes	Yes	Yes
Region dummies	No	Yes	No	Yes
Time controls	Yes	Yes	Yes	Yes
Woreda fixed effects	Yes	No	Yes	No
F-statistics	11.76***	79.14***	8.19***	79.14***
R squared	0.23	0.14	0.21	0.14
Observations	3969	3969	3969	3969

Notes: 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 dependent variables are income and per capita income. The instrumental variables used in the 2SLS regression are the neighbour's participation in agro-clusters and awareness of the existence of agro-clusters.

Robust standard errors are in parentheses; *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

5.2 | Regression results

5.2.1 | Effect of agro-clusters on income and per capita income

The OLS and IV estimates of the association between agro-clusters and income are presented in Table 3. The full results are provided in the Appendix S1. Belonging to an agro-cluster is positively associated with higher household and per capita income. The signs and magnitudes of the estimated coefficients are similar for both OLS and IV regressions. This may already suggest the robustness of the findings because OLS and IV estimate different effects. Looking at the IV estimates, a 0.1 increase in the share of land allocated to agro-clusters increases household income by approximately US\$104, and per capita income by about US\$16.

TABLE 4 Effect of agro-clusters on income poverty and income poverty gap

	Income poverty		Income poverty gap	
	LPM	IV	OLS	IV
Agro-clusters (0–1)	–0.20*** (0.04)	–0.20*** (0.10)	–0.13*** (0.04)	–0.29*** (0.08)
Additional controls	Yes	Yes	Yes	Yes
Crop dummies	Yes	Yes	Yes	Yes
Region dummies	No	Yes	No	Yes
Time controls	Yes	Yes	Yes	Yes
Woreda fixed effect	Yes	No	Yes	No
F-statistics	50.20	79.14	72.22	78.69
R squared	0.36	0.25	0.43	0.28
Observations	3969	3969	3966	3966

Notes: 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 dependent variables are income poverty and income poverty gap. The instrumental variables used in the 2SLS regression are the neighbour's participation in agro-clusters and awareness of the existence of agro-clusters.

Robust standard errors are in parentheses; *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

5.2.2 | Effect of agro-clusters on poverty

Table 4 shows the relationship between agro-clusters and the poverty indices. Here, similar findings are again obtained when using both OLS and IV regressions. The results on income poverty indicate that agro-clusters reduce poverty by about 2.0 percentage points. A percentage point increase in the share of land allocated to agro-clusters reduces the income poverty gap by about 2.9 percentage points. These findings align with Wardhana et al. (2017), who found that agro-clusters reduce poverty rates in Indonesia, with significant spillover effects.

Although clustering is clearly beneficial to smallholder farmers, it may also have implications and far-reaching benefits to governments and development actors by making their job of providing farm support services and coordination more effective and less costly. Focusing more on the benefits to smallholder farmers, an increase in incomes could arise from reduction in production costs arising from economies of scale and the use of labour-saving techniques. Such techniques may not only reduce costs but also provide more farm flexibility and product standardisation.

5.3 | Results on effect heterogeneity

Looking at effect heterogeneity using quantile regressions, all households (poor and non-poor) benefit from participating in agro-clusters. However, high-income and wealthy households obtain the most significant gains. As shown in Figure 1 panel A, the benefits from belonging to agro-clusters increase steadily across the income quantiles. This is similarly the case for the per capita income outcome, as shown in panel B. The results show that higher-income households may benefit more than low-income households, who are the intended targets. Nevertheless, with insights from the average and heterogeneous effects, agro-clusters may be instrumental in reducing rural poverty. Still, more emphasis needs to be placed on critically targeting and including the poor.

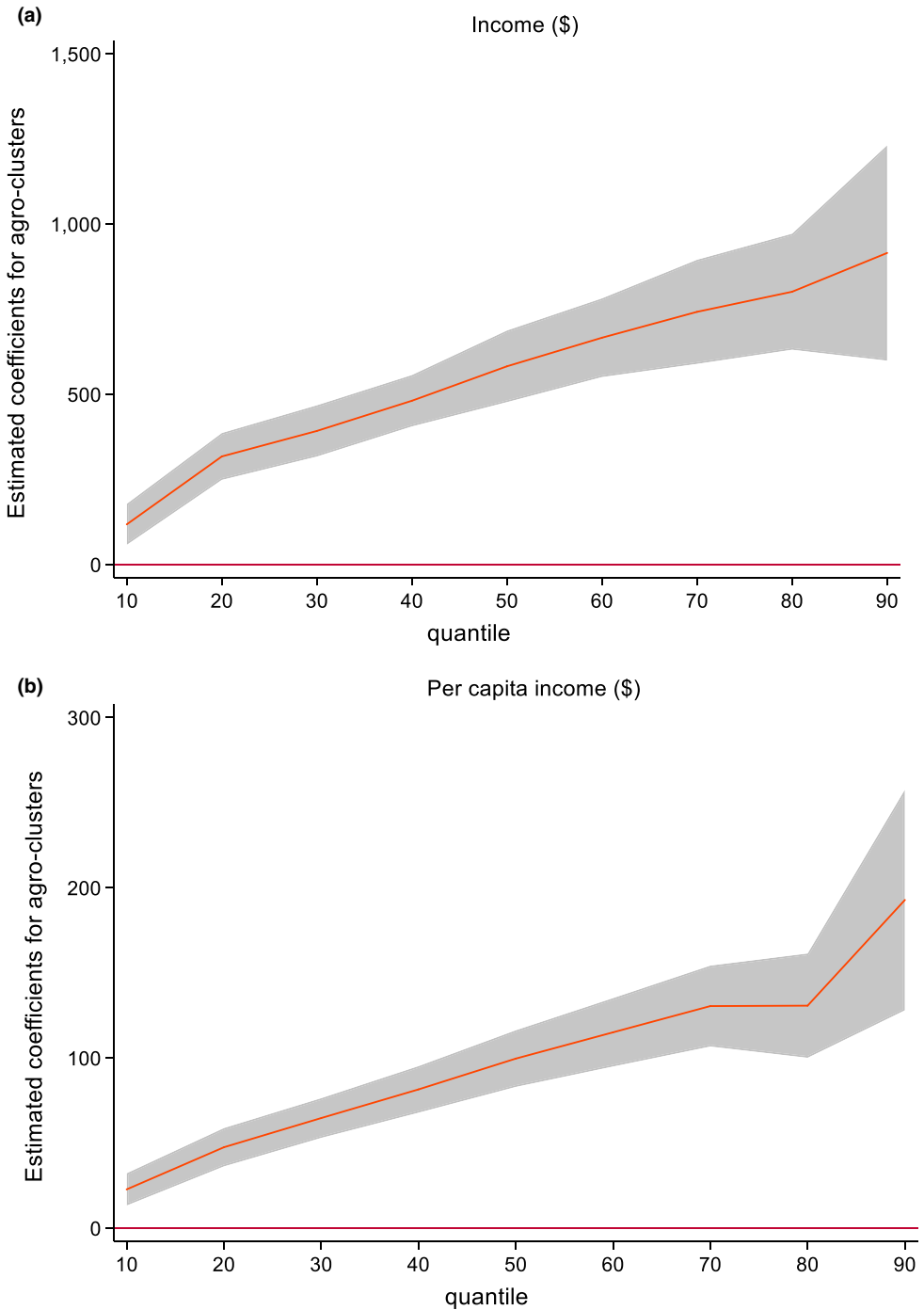


FIGURE 1 Quantile regression estimates for income and per capita income. The shaded areas indicate 95% confidence intervals, and the orange line is the effect line [Colour figure can be viewed at wileyonlinelibrary.com]

5.4 | Coefficient stability and unobserved selection

The stability of the estimates is tested through the inclusion of different farm household controls. If we assume that selection on observables is informative about selection on unobservables, simply evaluating and observing coefficient movements may be sufficient to say something about omitted variable bias. Beyond adding relevant controls and observing such coefficient movements, we follow the procedures of Altonji et al. (2005) and Oster (2019) in estimating how large omitted variable bias, in comparison with the inclusion of observed characteristics, can render the estimated coefficients as invalid.

To estimate this bias, first, values for R^2 are assumed and used to compute the delta value, for which the bias-adjusted estimates (beta) will be zero. The delta value here indicates how large unobserved selection must be, relative to observed selection, to explain away the estimated coefficients (Oster, 2019). Second, we now shift to the calculated bounds on beta based on the bounds of R^2 and delta. Broadly, this indicates how the main estimates will change if omitted variable bias is as strong as the inclusion of relevant controls. These bias-adjusted estimates are then compared with the true estimates to observe deviations. We follow Oster (2019) to establish the bounds on R^2 , which sets the R_{max} to be equal to 1.3 [R^2].

As shown in Table 5, the bias-adjusted estimates for the income coefficient are only slightly lower than the true estimated coefficient, which can be regarded as a lower bound of the true estimated effect. For income poverty, the coefficients are also just slightly lower, suggesting the stability of the estimated coefficients. Next, the delta coefficients indicate how much unobserved selection is needed relative to observed selection to explain away the estimated relationship between agro-clusters and poverty; the coefficients of 4.18 and 3.19 are estimated for income and income poverty, respectively. These coefficients indicate that omitted variable bias will have to be approximately 4.2 times the observed selection to nullify the estimated positive association between agro-clusters and income. Similarly, it would have to be 3.2 times the observed selection to explain away the negative association between agro-clusters and income poverty.

5.5 | Robustness checks

Several checks are performed to establish the robustness of our findings. Although using the share of land allocated to clusters may be the best metric to proxy for clusters in this analysis, the actual amount of land allocated to the cluster is also considered as a robustness check. The models were estimated with the same controls, and only the IV regressions were estimated, as

TABLE 5 Effect of agro-clusters on income poverty and income poverty gap

	Income		Income poverty	
	(1)	(2)	(3)	(4)
Beta adjusted coefficients	0	1250	0	-0.16
Delta	4.18	1	3.19	1
R^2 max	0.29	0.29	0.44	0.44
Observations	3969	3969	3969	3969

Notes: In specifications (1) and (3), the degree of omitted variable bias is calculated after setting the estimated coefficients to zero. In specifications (2) and (4), the omitted variable bias is assumed to equal the additional controls used, from which bias-adjusted beta coefficients are estimated. Robust standard errors are in parentheses: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

shown in the [Appendix SI](#). These estimates also indicate that agro-clusters increase income and reduce poverty.

Furthermore, agro-clusters are considered as a dummy variable, and selection on observables regressions are performed, which generally controls for self-selection into such programmes as agro-clusters, based on observable characteristics. The most commonly used estimators are matching and weighting estimators; however, these estimators would estimate biased effects if the treatment or the outcome model is not correctly specified (Wooldridge, 2007). Double robust estimators offer the promise of providing unbiased estimates when either the treatment or the outcome model is not correctly specified (Funk et al., 2011). Thus, the augmented inverse probability weighting estimator is used in estimating the effects of agro-cluster participation on income and poverty.

The double robust estimates are presented in [Table 6](#). When considering agro-clusters from a binary perspective, with no consideration of the actual amount of land allocated by the farmer or the share of total land allocated, the findings still indicate the income-increasing ability of agro-clusters. The poverty-reducing ability of agro-clusters is further strengthened as statistically meaningful estimates are still observable. These robustness checks further support the main findings that agro-clusters improve smallholder welfare and reduce rural poverty in Ethiopia.

6 | POLICY IMPLICATIONS

Our analysis suggests that agro-clusters may be useful in increasing smallholder incomes and reducing poverty. Fostering or scaling up agro-clusters may require strengthening rural and community institutions, such as access to land, extension support and financial services. Moreover, access to financial and credit services may potentially help to avoid regressive income effects that may lead to economic inequality. So, it will be helpful to focus these services specifically to move poor and vulnerable households from their current conditions. Strengthening the extension and outreach system will also benefit smallholder farmers by improving knowledge and understanding of agro-clusters and encouraging participation.

Given the disparities in income benefits, agricultural and development policies must consider heterogeneous household groups and resource levels when promoting agro-clusters. As agro-clusters can provide different welfare gains to diverse smallholder households, it is crucial to adjust and tailor activities to local needs and ensure that the poorest, as the intended

TABLE 6 Double robust estimates of the effects of agro-clusters

	Income	Per capita income	Income poverty	Income poverty gap
Agro-clusters (0/1)	269.96*** (89.68)	58.88*** (15.97)	-0.07*** (0.02)	-0.06*** (0.02)
Additional controls	Yes	Yes	Yes	Yes
Crop dummies	Yes	Yes	Yes	Yes
Region dummies	Yes	Yes	Yes	Yes
Time controls	Yes	Yes	Yes	Yes
Observation	3969	3969	3969	3969

Notes: 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, neighbour participation in agro-clusters, and awareness of the existence of agro-clusters. The controls are included to increase the precision of the regression estimates. The dependent variables are income, per capita income, income poverty, and income poverty gap. Robust standard errors are in parentheses; *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

targets, benefit. Policy-makers should also prioritise infrastructure improvements to improve connectivity between neighbouring agro-clusters so as to improve interaction and learning, as well as between agro-clusters and financial and market facilities to ensure long-term economic gains. It will be important for policy to also consider how to connect these agro-clusters with other development programmes, such as agro-industrial parks, which have the potential to create long-term market opportunities for the agro-clusters.

7 | CONCLUSIONS

In this paper, we examine the relationship between agro-clusters and rural poverty using a large household data from four Ethiopian regions where households cultivate cereals such as maize, wheat, teff, maltbarley and sesame. OLS and IV regressions were used to estimate the association of agro-clusters and rural poverty. Our results show that agro-cluster participation increases income and reduces poverty. These findings are robust to alternative estimators, such as augmented inverse probability weighting regression and different measures and proxies of agro-clusters. The results are unlikely subject to omitted variable bias. In the interest of unpacking heterogeneous effects, quantile regressions were also estimated, showing that agro-clusters increase income and reduce poverty for all income groups, though most significant gains are observed for the rich and wealthier households.

This study has two limitations that future research could address. First, despite employing different specifications that point to the results' robustness, the use of cross-sectional data makes it difficult to eliminate all forms of endogeneity. Various strategies and methods have been used in this regard, but we note that our estimates remain associations. As this is one of the first evaluations of agro-clusters, future research should use methods that improve identification and causality. Secondly, as context always matters, caution should be used when drawing generalisations from the analysis. Although the study's analysis is from a smallholder rural farm household perspective prevalent in many developing nations, it will be essential to build on the finding's external validity in other contexts.

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REFERENCES

- Altonji, J.G., Elder, T.E. & Taber, C.R. (2005) An evaluation of instrumental variable strategies for estimating the effects of Catholic schooling. *The Journal of Human Resources*, 4, 791–821. <https://doi.org/10.3368/jhr.XL.4.791>
- ATA. (2019) *Agricultural Transformation Agenda: 'Annual Report 2016–17*. Addis Ababa, Ethiopia: Ethiopian Agricultural Transformation Agency. Available online at www.ata.gov.et.
- Barrett, C.B., Carter, M., Chavas, J.-P. & Carter, M.R. (2019) *The economics of poverty traps*. Chicago, IL: University of Chicago Press.
- Brasier, K.J., Goetz, S., Smith, L.A., Ames, M., Green, J., Kelsey, T. et al. (2007) Small farm clusters and pathways to rural community sustainability. *Community Development*, 38(3), 8–22. <https://doi.org/10.1080/15575330709489826>

- Burger, K. (1999) Clustering of small agro-processing firms in Indonesia. *The International Food and Agribusiness Management Review*, 2(3–4), 289–299. [https://doi.org/10.1016/S1096-7508\(01\)00033-7](https://doi.org/10.1016/S1096-7508(01)00033-7)
- CSA. (2020) *Area and production of crops, and farm management practices*. Addis Ababa, Ethiopia: CSA.
- Dang, H.-A.H. & Dabalén, A.L. (2019) Is poverty in Africa mostly chronic or transient? Evidence from synthetic panel data. *The Journal of Development Studies*, 55(7), 1527–1547. <https://doi.org/10.1080/00220388.2017.1417585>
- Dercon, S. & Gollin, D. (2014) Agriculture in African development. Theories and strategies. *Annual Review of Resource Economics*, 6(1), 471–492. <https://doi.org/10.1146/annurev-resource-100913-012706>
- Di Falco, S., Doku, A. & Mahajan, A. (2020) Peer effects and the choice of adaptation strategies. *Agricultural Economics*, 51(1), 17–30. <https://doi.org/10.1111/agec.12538>
- Dirven, M. (1999) Dairy clusters in Latin America in the context of globalization. *The International Food and Agribusiness Management Review*, 2(3–4), 301–313. [https://doi.org/10.1016/S1096-7508\(01\)00045-3](https://doi.org/10.1016/S1096-7508(01)00045-3)
- Funk, M.J., Westreich, D., Wiesen, C., Stürmer, T., Brookhart, M.A. & Davidian, M. (2011) doubly robust estimation of causal effects. *American Journal of Epidemiology*, 173(7), 761–767. <https://doi.org/10.1093/aje/kwq439>
- Galvez-Nogales, E. (2010) Agro-based clusters in developing countries: staying competitive in a globalized economy. In *Agricultural Management, Marketing and Finance Occasional Paper (FAO) (25)*.
- Galvez-Nogales, E. & Webber, M. (Eds.). (2017) *Territorial tools for agro-industry development. A sourcebook. Agrobased clusters. With assistance of K. Murphy*. Rome, Italy: FAO.
- Goetz, S.J., Shields, M. & (Cindy) Wang., Q. (2004) Agricultural and food industry clusters in the northeast U.S.: technical report. Regional rural development paper No. 26. In: *The northeast regional Center for Rural Development, College of Agricultural Sciences*. University Park, PA: The Pennsylvania State University.
- Joffre, O.M., de Vries, J.R., Klerkx, L. & Poortvliet, P.M. (2020) Why are cluster farmers adopting more aquaculture technologies and practices? The role of trust and interaction within shrimp farmers' networks in the Mekong Delta, Vietnam. *Aquaculture*, 523(July), 735181. <https://doi.org/10.1016/j.aquaculture.2020.735181>
- Joffre, O.M., Poortvliet, P.M. & Klerkx, L. (2019) To cluster or not to cluster farmers? Influences on network interactions, risk perceptions, and adoption of aquaculture practices. *Agricultural Systems*, 173(1), 151–160. <https://doi.org/10.1016/j.agsy.2019.02.011>
- Louhichi, K., Temursho, U., Colen, L., & Paloma, S.G. (2019) *Upscaling the productivity performance of the agricultural commercialization cluster initiative in Ethiopia*. Luxembourg: Publications Office of the European Union.
- Minten, B., Mohammed, B. & Tamru, S. (2020) Emerging medium-scale tenant farming, gig economies, and the COVID-19 disruption: the case of commercial vegetable clusters in Ethiopia. *The European Journal of Development Research*, 32(5), 1402–1429.
- Montiflor, M. O., Batt, P. J. and Murray-Prior, R. (2015) Socio-economic impact of cluster farming for small-holder farmers in southern Philippines. Curtin University of Technology, GPO box U1987, Perth WA 6845, Australia.
- Mwabu, G. & Thorbecke, E. (2004) Rural development, growth and poverty in Africa. *Journal of African Economies*, 13(suppl_1), i16–i65. <https://doi.org/10.1093/jae/ejh015>
- National Bank of Ethiopia. (2019) *Annual reports 2019–2020*. Addis Ababa, Ethiopia: National Bank of Ethiopia.
- Oster, E. (2019). Unobservable selection and coefficient stability. Theory and Evidence. *Journal of Business & Economic Statistics*, 37(2), 187–204. <https://doi.org/10.1080/07350015.2016.1227711>
- Porter, M.E. (1998) Clusters and the new economics of competition. *Harvard Business Review*, 76(6), 77–90.
- Poulton, C., Dorward, A. & Kydd, J. (2010) The future of small farms. New directions for services, institutions, and intermediation. *World Development*, 38(10), 1413–1428. <https://doi.org/10.1016/j.worlddev.2009.06.009>
- Ruml, A. & Qaim, M. (2021) New evidence regarding the effects of contract farming on agricultural labor use. *Agricultural Economics*, 52(1), 51–66.
- Steffens, V.C. (2016) *Potentials of agrarian cluster development for improving smallholder's income—a case study from the SAGCOT initiative in Tanzania*. Bachelor. University of Cologne, Cologne. Available online at https://geographie.uni-koeln.de/sites/geographie/user_upload/Bachelorarbeit_Steffens.pdf.
- Tabe-Ojong, M.P., Hauser, M. & Mausch, K. (2022) Does agricultural commercialisation increase asset and livestock accumulation on smallholder farms in Ethiopia? *Journal of Development Studies*, 5(4), 79–544. <https://doi.org/10.1080/00220388.2021.1983170>
- Tabe-Ojong, M.P., Mausch, K., Woldeyohanes, T.B. & Heckelei, T. (2021) Three hurdles towards commercialization: integrating subsistence chickpea producers in the market economy. *European Review of Agricultural Economics*, 5(4), 79. <https://doi.org/10.1093/erae/jbab023>
- Varawa, J.T, Pickering, A.S. and Singh, S. (2014) Small farmer groups (farm clusters) as a strategy to up-scale tilapia fish farm production in Fiji Islands. Secretariat of the Pacific Community, Fiji and Fiji Ministry of Fisheries and Forests.
- Wardhana, D., Ihle, R. & Heijman, W. (2017) Agro-clusters and rural poverty. A spatial perspective for West Java. *Bulletin of Indonesian Economic Studies*, 53(2), 161–186. <https://doi.org/10.1080/00074918.2017.1298722>

- Wardhana, D., Ihle, R. & Heijman, W. (2020) Farmer cooperation in agro-clusters. Evidence from Indonesia. *Agribusiness*, 36(4), 725–750. <https://doi.org/10.1002/agr.21637>
- Wooldridge, J.M. (1995) Score diagnostics for linear models estimated by two-stage least squares. In: Maddala, G.S., Phillips, P.C.B. & Srinivasan, T.N. (Eds.) *Advances in Econometrics and Quantitative Economics: Essays in Honor of Professor C. R. Rao*. Oxford: Blackwell, pp. 66–87.
- Wooldridge, J.M. (2007) Inverse probability weighted estimation for general missing data problems. *Journal of Econometrics*, 141(2), 1281–1301. <https://doi.org/10.1016/j.jeconom.2007.02.002>
- Zhang, X. & Hu, D. (2014) Overcoming successive bottlenecks: the evolution of a potato cluster in China. *World Development*, 63, 102–112.

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