Can Agricultural Cooperatives Reduce Poverty? Heterogeneous Impact of Cooperative Membership on Farmers' Welfare in Rwanda

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Abstract

We analyze the inclusiveness and effectiveness of agricultural cooperatives in Rwanda. We estimate mean income and poverty effects of cooperative membership using propensity score matching techniques. We analyze heterogeneous treatment effects across farmers by analyzing how estimated treatment effects vary over farm and farmer characteristics and over the estimated propensity score. We find that cooperative membership in general increases income and reduces poverty and that these effects are largest for larger farms and in more remote areas. We find evidence of a negative selection as impact is largest for farmers with the lowest propensity to be a cooperative member.

Keywords: cooperatives, agriculture, poverty, impact evaluation, Rwanda

JEL codes: Q12, Q13, I32, J54, O13

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Introduction

Improving the productivity, profitability and sustainability of smallholder agriculture is argued to be the main pathway out of rural poverty in developing countries. Institutional innovations are believed to play a crucial role in this as they can help farmers to overcome market failures (Hazell et al., 2010; World Bank, 2008). There is a renewed interest in producer organizations such as cooperatives as an institutional tool to improve market participation of smallholder farmers, increase farm incomes and reduce rural poverty (Bernard and Spielman, 2009; Bernard and Taffesse, 2012; Fisher and Qaim, 2012a&b; Markelova et al., 2009; Shiferaw et al., 2009). To have an effect on poverty, these emerging institutions need to be both, inclusive – i.e. poorer farmers need to participate – and effective – i.e. creating an impact on farmers' income and wellbeing. Cooperatives are often associated with collective action and social capital, and are therefore often thought to be more inclusive than other types of institutional innovations such as contract-farming.

Various empirical studies have verified how inclusive agricultural cooperatives are, and investigated which farmers are included in (or excluded from) cooperatives. In general, participation in agricultural cooperatives is found to be closely linked to human and social capital (Hellin et al., 2009). For example, some authors find that farmers' level of education, farmers' age, farming experience, access to social networks and information have a positive effect on the likelihood of cooperative membership (Bernard and Spielman, 2009; Fischer and Qaim, 2012a; Francesconi and Heerinck, 2010; Ito et al., 2012; Markelova and Mwangi, 2009; Matuschke and Qaim, 2009; Okello et al., 2007; Zheng et al., 2012). But physical capital and farmers' asset endowments matter as well. For example, land and livestock holdings are found to have a positive (but sometimes decreasing) effect on the likelihood of farmers to participate in agricultural cooperatives (Bernard and Spielman, 2009; Fischer and Qaim, 2012; Ito et al., 2012). Some studies conclude that the poorest farmers are excluded (e.g. Fischer and Qaim, 2012a; Francesconi and Heerinck, 2010; Ito et al., 2012; Quisumbing et al., 2008) while others point to a middle-class effect with both the poorest and the most wealthy farmers least likely to participate (Bernard and Spielman, 2009). The prevailing evidence suggests that agricultural cooperatives are to some extent exclusive.

Concerning the effectiveness of cooperatives to bring about output and income growth, studies have indicated positive effects of cooperative membership on producer prices and market participation, and on the likelihood to adopt improved technologies (e.g. Abebaw and Haile, 2013; Bernard et al., 2008; Bernard and Taffesse, 2012; Fisher and Qaim, 2012a; Francesconi and Heerink, 2010; Holloway et al., 2000; Ito et al., 2012; Shiferaw et al., 2009; Verhofstadt and Maertens, 2013; Wollni and Zeller, 2007). Some studies point to a positive impact on farm incomes and profits (e.g. Fisher and Qaim, 2012a; Ito et al., 2012; Vandeplas et al., 2013). Yet, the effects of cooperative membership on poverty have rarely been analyzed.

As the overall poverty impact of institutions hinges on both inclusion and effectiveness, it is important to look beyond mean treatment effects. Only a handful of studies has specifically analyzed how the impact of cooperative membership changes with farm and farmer characteristics. Bernard et al. (2008) find that cooperative membership leads to a higher degree of commercialization for cereal farmers in Ethiopia; but the effect is larger for the largest farms and even negative for very small farms. Ito et al. (2012) find that the impact of cooperative membership on farm income for watermelon farmers in China is twice as large for small farms than for larger farms. Fisher and Qaim (2012a) find that the effects of participating in banana cooperatives in Kenya on commercialization, technology adoption and farm income are more pronounced for the smallest farms. Abebaw and Haile (2013) study the impact of cooperative membership on the likelihood farmers use fertilizer in Ethiopia and find a stronger positive effect for less educated farmers and in more remote areas.

In this paper we look at membership of smallholder farmers in agricultural cooperatives in Rwanda and analyze the impact of this membership on household income and poverty. We look at mean income and poverty effects as well as at heterogeneous treatment effects across farmers. We use several propensity score matching techniques to estimate the average treatment effect of cooperative membership on farm income and the likelihood of being poor. We then analyze how the estimated treatment effect varies over various farm and farmer characteristics and over the estimated propensity score. We find that cooperative membership in general has a positive impact on farm income and a negative impact on the likelihood of being poor but that the effect varies with farm size, distance to the market, and the availability of labor in the household.

Our focus on Rwanda is particularly relevant because agricultural cooperatives are seen as an important institutional vehicle to improve the performance of the smallholder farm sector and to achieve rural poverty reduction (GoR, 2004; 2011). Their number has been increasing very rapidly during the past couple of years (USAID, 2013). A handful of qualitative studies has pointed out that cooperatives in Rwanda are exclusive and aggravate existing inequalities in rural communities (Ansoms, 2009 & 2010; Nabahungu and Visser, 2011; Pritchard, 2013). There are however very few studies that analyze the impact of cooperative membership on rural incomes and poverty reduction.

Our approach to look at heterogeneous treatment effects allows analyzing both inclusion and effectiveness of cooperatives in a comprehensive way. Examining heterogeneity in treatment effects stems from the program evaluation literature. The evaluation of development projects and public health programs (e.g. Basu et al., 2007; Behrman and Hoddinott, 2005; Lechner, 2002; Millimet and Tchernis, 2013) has moved beyond mean impact studies into studies analyzing the distribution of impacts within the treated subjects. Studying heterogonous treatment effects is important from the perspective of program targeting. If those participants who are most likely to benefit from a treatment are selected or self-select into treatment, expanding the group of treated subjects can reduce the average effectiveness of the treatment. If participants are those that are not most likely to benefit from the treatment, expanding the participant group or retargeting the program can increase the average treatment effect (Xie et al., 2012; Djebbari and Smith, 2008). Estimating heterogeneous treatment effects of cooperative membership can reveal whether there is positive or negative selection (Brand and Xie, 2013; Xie et al., 2010), which is important to understand how cooperatives can be more effective in reducing poverty.

Background and data collection

In Rwanda, the agricultural sector is a key engine for economic development and poverty reduction, contributing 34% to GDP and about 90% to employment (GoR, 2011; World Bank, 2011). Rwandan agricultural policies and strategies focus on intensification and increased market orientation of the smallholder agricultural sector, and cooperatives are seen as an important vehicle to achieve this (GoR, 2011). The number of agricultural cooperatives in the country has expanded very rapidly during the past couple of years, from 645 in 2008 to 2,400 in 2013 (USAID, 2013). Agricultural cooperatives include production cooperatives – where land is cultivated communally – as well as service cooperative such as land cooperatives[i] – where access to agricultural land is arranged communally – and marketing cooperatives – where marketing of farm produce is done communally – or a mixture of these. Agricultural cooperatives also play a role in distributing subsidized inputs, especially mineral fertilizer.

In this study we focus on land and marketing cooperatives in the Muhanga district in the Southern province of Rwanda (Figure 1), where most cooperatives are active in the maize and horticulture sectors. We use data from an original survey among 389 farm-households[ii], that was implemented in the period February - March 2012. Our sample includes 154 treated or cooperative member households and 235 control or non-member households, in 40 villages in the district of Muhanga. The treated household belong to 7 different cooperatives that can be defined as 'land and marketing cooperatives' as both access to land and marketing of produce are organized in a communal way. Production cooperatives are present in the region as well, but are not considered for this analysis. Farm households were selected through a three-stage stratified random sampling design with oversampling of cooperative member households.

We used a quantitative structured questionnaire, with specific modules on demographic characteristics, land and non-land asset holdings, agricultural production, off-farm employment, non-labor income, cooperative membership, savings and credit. The data allow to calculate farm income and total household income, and derive poverty figures. The household survey data were complemented with data from semi-structured interviews with the cooperatives in the sample on cooperative activities, investments, marketing strategies and organizational set-up.

Econometric approach

Propensity score matching

We use propensity score matching (PSM) to analyze the inclusiveness and effectiveness of cooperatives. This method allows us to analyze the likelihood of cooperative membership, the impact of cooperative membership on farm income and poverty, and the heterogeneity in impact across farmers in a comprehensive way.

First, we estimate the propensity score (PS) as the probability of the sampled farmers to be a member of an agricultural cooperative (D). We use a probit model and include a large set of conditioning factors (X) that can explain a possible non-random distribution of cooperative membership in the population:

$$\mathbf{PS= P(D=1|X)} \qquad \mathbf{(1)}$$

The variables included in the vector X relate to household demographic characteristics, household asset ownership, a social capital indicator and a market access indicator – as described in table 1.

The estimated PS can be interpreted as the probability of being a cooperative member and the estimated marginal effects as the impact of variables in X on this probability. The probit estimation will result in insights on whether cooperative membership is biased towards certain types of households and hence on the inclusiveness of cooperatives.

Second, we estimate average treatment effects (ATE) of cooperative membership on farm income and the likelihood of being poor. We use the estimated PS to match treated observations or cooperative member households with untreated observations or non-member households. We estimate average treatment effects as the average difference in farm income and poverty incidence between treated Y(1) and matched controls Y(0) (Dehejia and Wahba, 2002; Ichino, 2008; Imbens, 2004):

$$\mathbf{ATE = E[Y(1) - Y(0)] = E[Y(1)] - E[Y(0)]} \qquad \mathbf{(2)}$$

With this method, we compare the income and poverty of cooperative members or treated households with non-members or control households that are similar in terms of observable characteristics, and partially control for non-random selection of cooperative members (Imbens, 2004; Imbens and Angrist; 1995; Caliendo and Kopeinig, 2008). The estimated ATE can be interpreted as the impact of cooperative membership on farm income and poverty, and hence as the effectiveness of cooperatives.

Table 1. Conditioning factors used as covariates in the probit model estimating the propensity to be a cooperative member

Variable	Description
Demographic characteristics	
Female single HH	Dummy for single, female-headed households
HH head age (yrs)	Age of the household head in years
Square of HH head age	
HH head education (yrs)	Years of education of the household head
HH agricultural workers (#)	Number of agricultural workers in the household
HH children (#)	Number of children (age < 18 years) in the household
Asset ownership	
Land owned (ha)	The total area owned by the household, expressed in hectares
Square of land owned	
TLU	Number of tropical livestock units (TLU) possessed by the hh
Social capital	
Siblings close by (#)	The number of brothers and sisters of the household head and his/her partner living close by
Market access	
Distance to the market (min)	The mean distance to the market, expressed in minutes of walking distance, of the plots under cultivation

PSM methods are sensitive to the exact specification and matching method (Imbens, 2004; Caliendo and Kopeinig, 2004). Therefore, as robustness check, we use four different matching techniques that are commonly used in PSM: nearest neighbor matching with one neighbor, nearest neighbor matching with three neighbors, kernel matching and local linear matching. With a single-nearest neighbor matching every treated household is matched to the control household with the closest PS. With a three-nearest neighbor matching every treated household is matched to three households that are closest in PS and Y(0) is calculated as the average of the three matched controls. Matching is done with replacement to assure that each treatment unit is matched to the control unit with the closest PS, which reduces bias (Dehejia and Wahba, 2002). Kernel matching[iii] uses a weighted average of all individuals in the control group to construct Y(0), with weights inversely proportional to the PS distance between treated and control units. This method uses more information to construct the counterfactual outcome Y(0), which will result in reduced variance but increased bias in case of poorer matching (Caliendo and Kopeinig, 2004). Local linear matching compares to kernel matching but uses an additional linear term in the weighing function, which helps to avoid bias when the PS of control observations are distributed asymmetrically around the treated observations.

Third, we analyze how the estimated income and poverty effects of cooperative membership differ across farmers. We apply methods[iv] proposed by Abebaw and Haile (2013), Bernard et al. (2008), and Mutuc et al. (2013). We calculate the average treatment effect on the treated (ATT), which measures the impact of cooperative membership on farm income and poverty for actual cooperative members only:

$$\mathbf{ATT = E[Y(1) - Y(0)|D=1] = E[Y(1)\ |D=1] - E[Y(0)\ |D=1]} \qquad \mathbf{(3)}$$

We use the estimated ATT, generated using the kernel matching method, as dependent variable in a linear regression model and analyze how the estimated income and poverty effects vary with the estimated propensity score, and with farm and farmer characteristics. We visually inspect impact heterogeneity by plotting the ATT over the PS distribution and over the distribution in farm and farmer characteristics, and derive a smoothed curve. We use the following farm and farmer characteristics: the age, education and gender of the household head, the agricultural labor force in the household, the size of the household's owned plots and the distance to the market. These graphical and statistical analyses will reveal for which type of farmers cooperative membership has the largest impact on income and poverty, and hence whether cooperatives are most effective for those most likely to participate – or not.

Assumptions

The reliability of PSM estimators depends on two crucial assumptions. First, the common support or overlap condition requires balancing in the covariate distribution between treated and untreated observations to ensure that treatment observations have comparable control observations nearby in the PS distribution (Caliendo and Kopeinig, 2008). The propensity score distribution shows sufficient overlap between treated and controls. As proposed by Heckman et al. (1997) and Becker and Ichino (2002), we only use observations in the common support region, where the PS of the control units is not smaller than the minimum PS of the treated units and the PS of the treated units not larger than the maximum PS of the control units (Becker and Ichino, 2002). We investigate the balancing properties of the covariates for the case of kernel matching and find that matching eliminates all imbalances between treated and controls.

Second, the conditional independence assumption states that given a set of observable covariates, potential outcomes are independent of treatment assignment (Imbens, 2004). This implies that selection into treatment is based entirely on observable covariates, which is a strong assumption. We perform a simulation-based sensitivity analysis (Ichino et al., 2008; Ito et al., 2012; Maertens et al., 2011) and find that our results are robust to failure of the conditional independence assumption.

Results and discussion

Comparison of cooperative members and non-members

In Table 2 we compare cooperative members with non-member households in terms of observable characteristics. Cooperative member households have a relatively older household head and more agricultural labor force in the household. In general, 22% of households in the sample are single female-headed, which is in line with the 27.7% single female headed households in the Muhanga district reported by the recent national EICV results (NISR, 2012). There are significantly less female headed households among the cooperative member households. There are no significant differences in the education of the household head, the number of children in the household, the distance to the market and the number of siblings close by (as a measure of social capital). We find that land- and livestock holdings in general are quite small, with on average 0.27 ha of land and 1.1 tropical livestock units per household. Cooperative members have significantly more livestock than non- members, 1.8 units on average compared to 0.8 units. Cooperative members have on average 0.34 ha of land compared to 0.25 ha for non-member households, but this difference is statistically not significant. In addition to the land they own, cooperative members cultivate on average an additional 0.1 ha of land they access through the cooperative.

Cooperative members and non-member households differ substantially with respect to income and poverty levels. Farm income is significantly larger for cooperative members than for non-members: 400,422 RWF for members compared to 176,682 RWF for non-members. Poverty is widespread in our research area and almost half of the households in the sample are poor. While 34% of cooperative member households are poor, the incidence of poverty is significantly higher (54%) among non-member households.

Table 2. Characteristics of cooperative member and non-member households

	Total sample (N=389)	Non-member households (N=235)	Cooperative member households (N=154)
Demographic characteristics			
Female single headed (dummy)	22%	25%	11%*
HH head age (years)	45.6	44.6	49.0*
	(13.3)	(13.6)	(11.7)
HH head education (yrs)	4.9	4.7	5.4
	(2.9)	(2.7)	(3.3)
HH size agricultural workers (#)	1.9	1.8	2.4***
	(0.98)	(0.88)	(1.2)
HH size children (#)	2.5	2.6	2.4
	(1.7)	(1.7)	(1.8)
Asset ownership			
Land individually owned (ha)	0.27	0.25	0.34
	(0.50)	(0.48)	(0.54)
Livestock (TLU)	1.1	0.8	1.8***
	(1.1)	(0.9)	(1.5)
Market access			
Distance to the market (min)	47	46	49
	(33)	(32)	(37)
Social capital			
Siblings living close by(#)	2.2	2.1	2.5
	(2.5)	(2.5)	(2.5)
Income and poverty			
Farm income (RWF)	229,529	176,682	400,422**
	(307,653)	(194,161)	(491,565)
Poverty incidence	49%	54%	34%**

Notes: Mean values are shown, for continuous variables standard deviations are shown in parentheses. Cooperative member households are compared to non-member households using t-test, *, ** and *** denote 10, 5 and 1% significance level. Annual farm income is calculated as the value of crop and livestock production (including non-marketed produce valued at market prices) minus variable production costs (including purchased inputs, hired labor, land rent, etc.). Revenue transfers from the cooperatives are also added to the farm income while cooperative contribution cost are subtracted. The poverty line is set at 83,000 RWF per adult equivalent per year, which is the Rwandan national poverty line for extreme poverty derived from the 2011 EICV3 survey.
Source: calculations based on household survey data collected in 2012

Probability of cooperative membership

The results of the probit model estimating the propensity of cooperative membership are given in Table 3. Marginal effects are reported. We find that households with a more educated head and households with more agricultural labor force have a higher probability of being member of a cooperative. The estimated marginal effects indicate that an additional year of education of the household head increases the likelihood of cooperative membership with 2.2 percentage points, and an additional agricultural laborer in the household with 7.2 percentage points. Further, we find that owning more land decreases the likelihood of being a cooperative member while owning more livestock increases it. An additional ha of land decreases the likelihood of cooperative membership with 19% points and an additional unit of livestock increases it with 9.1% points. Distance to the market has a significant negative effect on the probability of cooperative membership, with every hour further away from the market decreasing the likelihood of cooperative membership with 12 percentage points. Other variables such as the gender and the age of the household head, the number of children in the household and the social capital indicator do not have a significant impact on the likelihood of cooperative membership.

Table 3. Probit regression results estimating the propensity of cooperative membership

Variables	marginal effects		standard errors
Female single HH	-0.058		0.062
HH head age (yrs)	0.007		0.013
Square of HH head age	0.000		0.000
HH head education (yrs)	0.022	***	0.007
HH agricultural workers (#)	0.072	***	0.024
HH children (#)	-0.024		0.015
Land owned (ha)	-0.190	**	0.090
Square of land owned	0.033		0.022
TLU	0.091	***	0.020
Distance to the market (min)	-0.002	**	0.001
siblings close by (#)	0.001		0.011
Pseudo-R2	0.118		
LR chi2 (11)	61.8		
Prob > chi2	0.000		
Observations	389		

Note: *, ** and *** denote 10, 5 and 1% significance level, respectively. Estimated marginal effects are reported.
Source: estimations based on household survey data collected in 2012

These results indicate that the agricultural cooperatives under study are to some extent exclusive. There seems to be entry constraints especially in terms of human capital. Also, remoteness seems to be a constraints for cooperative membership. Farm-households further away from the market are less likely to be organized in cooperatives while those households face higher transactions costs, which likely makes cooperative marketing and input acquisition more beneficial. The results are less clear on whether wealth and physical capital are a constraint for cooperative membership or not. The positive effect of livestock ownership indicates that relatively poorer households face constraints to enter cooperatives while the negative effect of land ownership indicates the opposite. The latter effect might also imply that access to cooperative land is a main driving force for land-poor households to participate in cooperatives.

Income and poverty effects of cooperative membership

The estimated average treatment effects (ATE) are presented in Table 4. It is important to note that the estimated ATEs are consistent over different matching techniques, which is an indication of the robustness of the PSM estimates. The estimated effect of cooperative membership on farm income, respectively the likelihood of being poor, are significantly positive, respectively negative, and similar in magnitude across the matching methods. We find that cooperative membership increases farm income with 40 to 46% and reduces the likelihood of being poor with 10 to 14% points. These are large and important effects that lead to the conclusion that agricultural land and marketing cooperatives are effective in improving farmers' welfare.

Table 4. Estimated average treatment effects of cooperative membership

Dependent variables	Single-nearest neighbor matching	Three-nearest neighbor matching	Kernel Matching	Local linear Matching
log (farm income)	0.43***	0.40***	0.40***	0.46***
	(0.15)	(0.16)	(0.14)	(0.14)
Poverty	-0.10**	-0.14**	-0.12**	-0.13**
	(0.050)	(0.069)	(0.056)	(0.055)

Notes: Standard errors are shown in parentheses. Significant effects are indicated with * : p ≤ 0.1; ** : p ≤ 0.05; *** : p ≤0.01.
Source: estimations based on household survey data collected in 2012

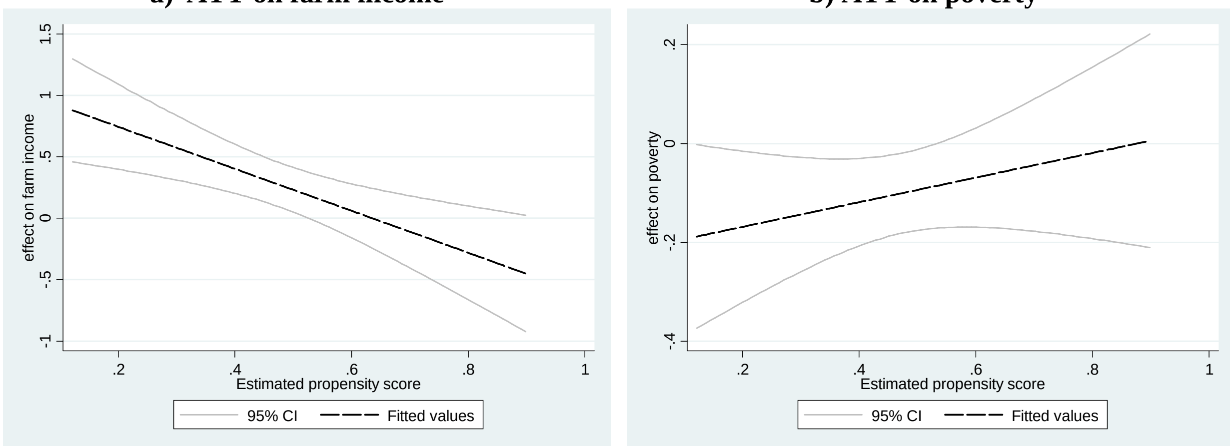
Heterogeneous treatment effects

The results of the graphical and statistical analyses of heterogeneous treatment effects are given in figure 1 to 4. We consecutively discuss the results for heterogeneity over the PS, land ownership, market access and demographic characteristics.

Heterogeneity over the propensity score

Figure 1 shows how the estimated income and poverty effects vary over the estimated propensity score. The results indicate that the ATT on farm income varies significantly with the propensity score and that the slope is negative. This means that the effect of cooperative membership on farm income is largest for households with the lowest propensity to be a cooperative member, and decreases with the propensity of cooperative membership. The slope coefficient is estimated to be 1.7, which means that with every 10% points increase in the likelihood of cooperative membership, the impact of this membership on income reduces with 17 percent. The income effect of cooperative membership even becomes zero in the upper end of the PS distribution. The ATT on the likelihood to be poor increases with the estimated propensity score but the slope coefficient is not significant.

a) ATT on farm income | **b) ATT on poverty**



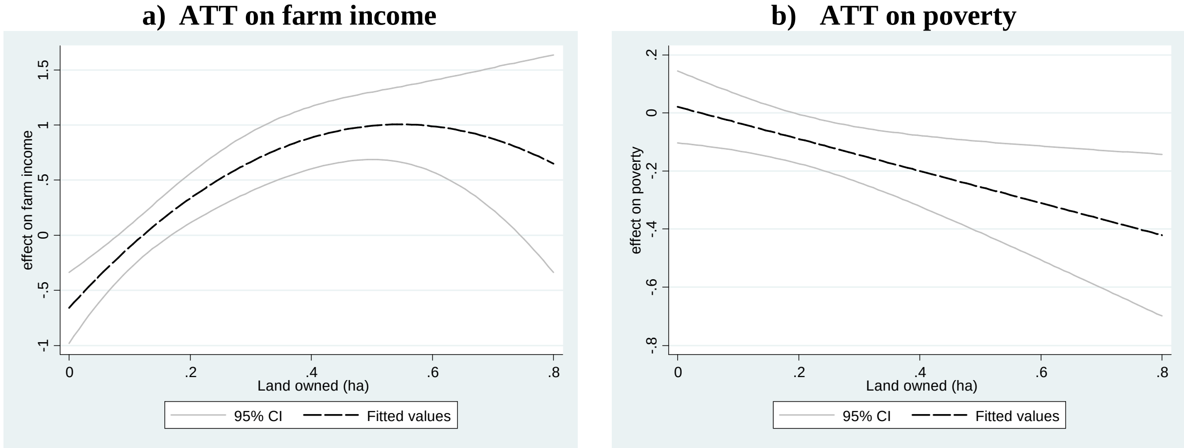
$ATT = -1.71^{***}x + 1.09^{***}$ | $ATT = 0.25x - 0.22^{*}$

Figure 1. Heterogeneity of treatment effects over the propensity to be a cooperative member
Notes: Linear and quadratic prediction plots with 95% confidence intervals.

These results point to a problem of negative selection. Cooperatives are most effective in increasing the incomes of farmers that are least likely to join cooperatives, and or least effective – or even not effective at all – in increasing the incomes of farmers who are most likely to join. In other words, farmers who would gain most from cooperative membership are the least likely to join, likely because they face entry constraints in terms of human and physical capital. The subsequent analyses on impact heterogeneity over different farm and farmer characteristics can shed further light on this finding of negative selection.

Heterogeneity over land ownership

Figure 2 shows how the estimated income and poverty effects vary with households' landownership[v]. The results indicate that there is an inverse U-shaped relation between land and the estimated ATT on farm income. The impact of cooperative membership on farm income is increasing with landownership up to landholdings of about 0.5 ha, and decreasing thereafter. As about 80% of the sampled households own less than 0.5 ha of land, the income effect of cooperative membership is largely increasing with households' landholdings but at a decreasing rate. The estimated income effect becomes zero at the lower end of the land distribution, from landholdings of about 0.15 ha onwards. Further, the results indicate that the estimated ATT on the likelihood to be poor significantly decreases with landholdings. Hence, the poverty reducing effect of cooperative membership increases with land. Again, we find that the ATT becomes zero for very small landholdings.



$ATT = -5.57^{***}x^2 + 6.09^{***}x - 0.66^{***}$ $ATT = -0.55^{***}x + 0.022$

Figure 2. Heterogeneity of treatment effects over landownership
Notes: Linear and quadratic prediction plots with 95% confidence intervals.

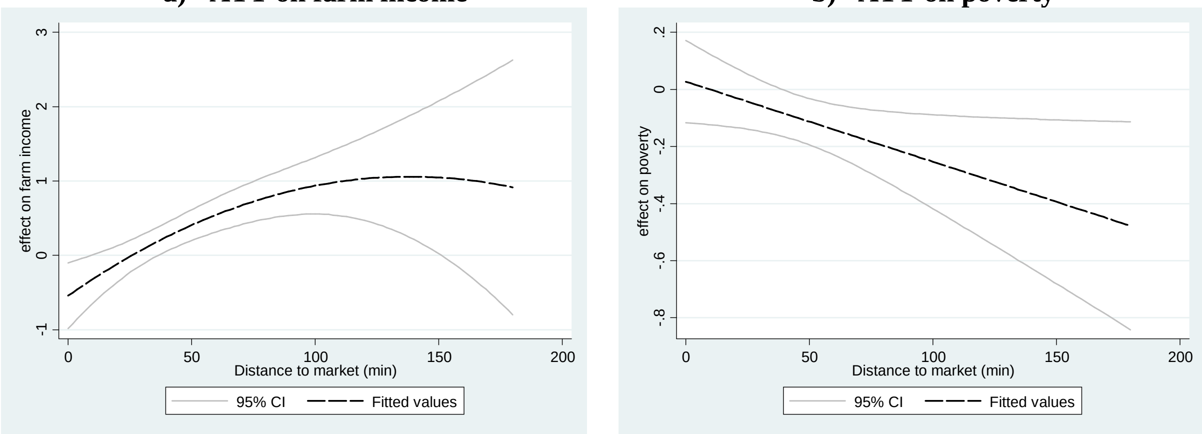
These findings imply that the cooperatives under study are most effective in increasing farm income and reducing poverty among smallholders with relatively larger landholdings. For land-poor or near-landless farmers, cooperative membership is not effective for improving welfare. These results contradict findings by Ito et al. (2012) and Fischer and Qaim (2012) who demonstrate that cooperative membership in China and Kenya has a larger impact for smaller farms. Given our finding from section 4.2. that land ownership has a negative impact on the propensity to be a cooperative member, the results in figure 2 contribute to explaining the observed negative selection. While households with the smallest landholdings have the highest propensity to join a cooperative, the impact of cooperative membership on their incomes is very small, and not enough to lead to poverty reduction. Other authors also pointed to negative selection related to farm size but in the opposite direction. Ito et al. (2012) and Fischer and Qaim (2012) find that the income gains of cooperative membership are more pronounced for small farmers who have a lower propensity to join cooperatives.

A possible explanation for our findings lies in the fact that landholdings are very small in our study area; on average households own only 0.27 ha. Cooperative membership, even if it improves the access to land through cooperative land acquisition (on average 0.1 ha), does not have an impact on farm income for very small farms. These farms use few inputs and commercialize small amounts of produce, such that reductions in transactions costs due to cooperative marketing and input purchase are only marginal.

Heterogeneity over market access

Figure 3 shows how the estimated income and poverty effects vary with distance to the market. We find an inverse U-shaped relation between market access and the estimated ATT on farm income. The impact of cooperative membership on farm income is increasing with distance to the market up to a distance of about 2 hours (116 minutes is the turning point), and decreasing thereafter. In addition, the estimated ATT on the likelihood to be poor significantly decreases with distance to the market, meaning that the poverty reducing effect of cooperative membership increases with distance to the market. Both the income effect and the poverty effect become very small and close to zero for households located very close to the market.

a) ATT on farm income **b) ATT on poverty**



$ATT = -0.0001^{*}x^2 + 0.023^{***}x - 0.54^{**}$ $ATT = -0.0028^{**}x + 0.073$

Figure 3. Heterogeneity of treatment effects over market access
Notes: Linear and quadratic prediction plots with 95% confidence intervals.

Our findings imply that cooperatives are most effective in more remote areas. As transaction costs are larger in remote areas, cooperative marketing and input acquisition can create larger gains through reductions in transaction costs. Our findings are in line with those of Adebaw and Haile (2013) who point to an inverse U-shaped relation between distance to the nearest road and the impact of cooperative membership on technology adoption in Ethiopia. Given our finding from section 4.2. that distance to the market significantly reduces households' propensity to be a cooperative member, the results in figure 3 contribute to explaining negative selection. Farmers in more remote areas are less likely to join cooperatives while the potential benefits are largest for them.

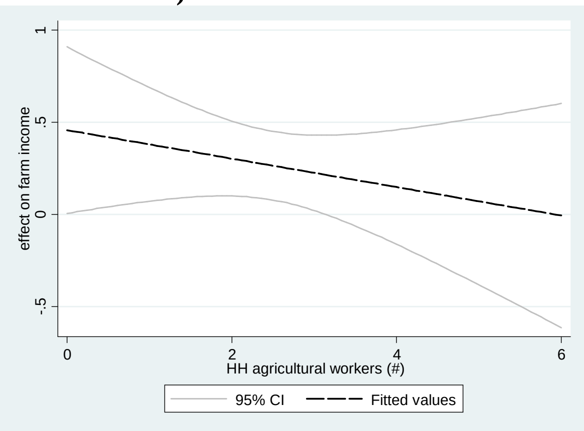
Heterogeneity over demographic characteristics

Figure 4 shows how the estimated income and poverty effects vary with some demographic characteristics of farm-households. The estimated ATT on farm income does not vary with the considered demographic characteristics, age and education of the household head and the available labor force, as none of the effects are significant. In addition, we tested whether the estimated ATTs differ according to the gender of the household head[vi] and find no significant differences. These findings contradict the findings of Adebaw and Haile (2013) that the impact of cooperative membership decreases with farmers' education; but are in line with the findings of Bernard et al. (2008). The results imply that cooperatives are as effective in creating welfare gains for less educated farmers as for more educated farmers, as effective for younger and less experienced farmers as for older and more experienced farmers, and as effective for male as for female headed farm-households.

The estimated ATT on the likelihood to be poor significantly increases with the available agricultural labor in the household. Hence, the poverty reducing effect of cooperative membership is largest for households with few agricultural laborers – likely because these are the poorest households, and not because the income gains are largest for these households.

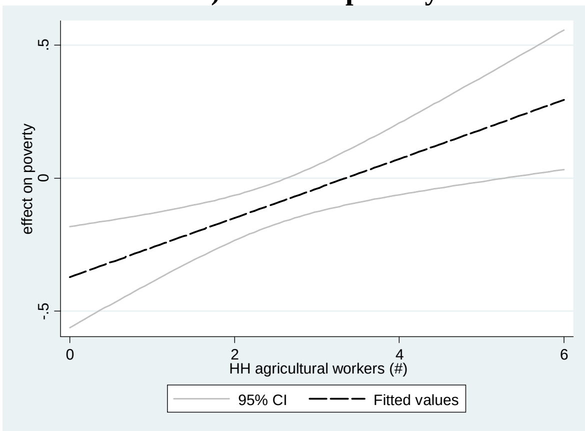
I. Heterogeneity over agricultural labour force

a) ATT on farm income



$ATT = 0.077\ x + 0.46^{**}$

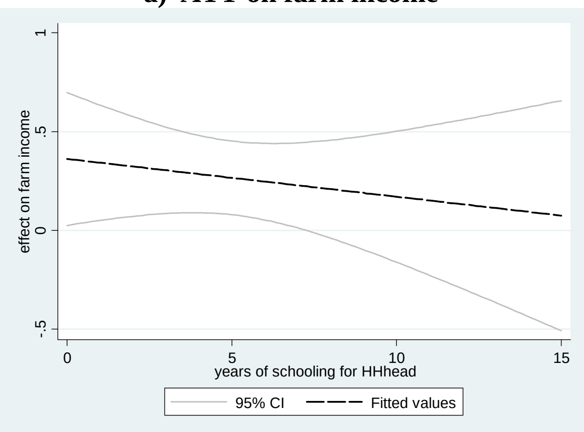
b) ATT on poverty



$ATT = 0.11^{***}x - 0.37^{***}$

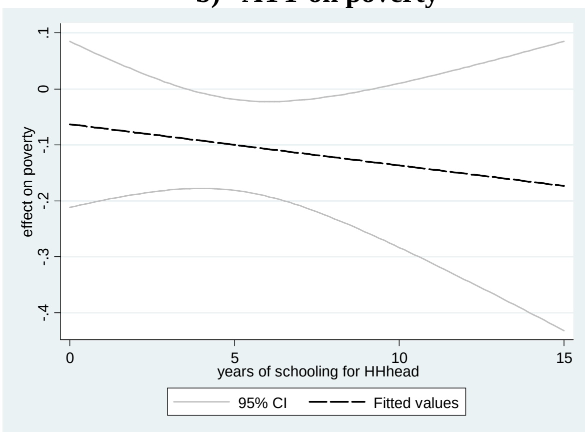
II. Heterogeneity over farmers' education

a) ATT on farm income



$ATT = -0.019x - 0.36^{**}$

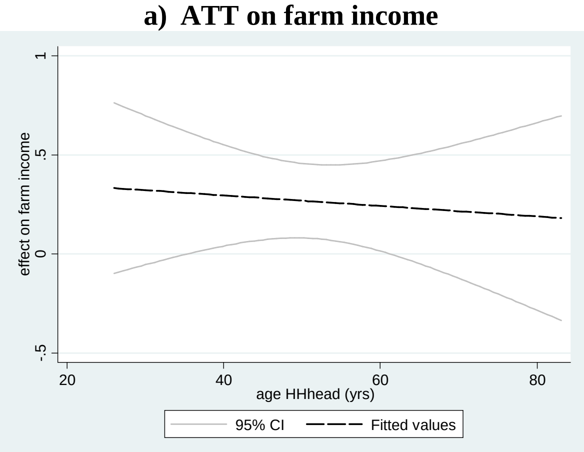
b) ATT on poverty



$ATT = -0.0073x - 0.063$

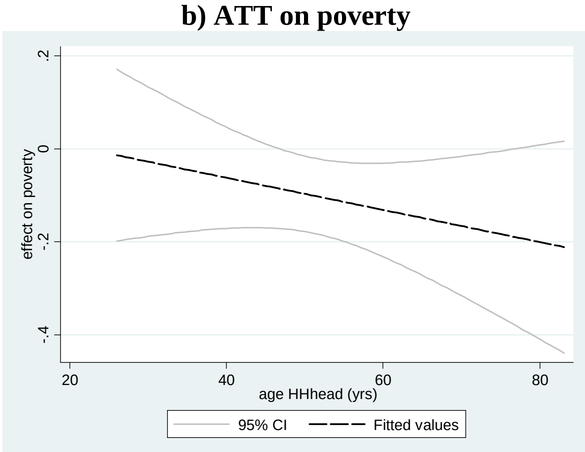
III. Heterogeneity over farmers' age

a) ATT on farm income



$ATT = -0.0027x + 0.40$

b) ATT on poverty



$ATT = -0.0035x + 0.076$

Figure 4. Heterogeneity of treatment effects over demographic characteristics

Notes: Linear and quadratic prediction plots with 95% confidence intervals.

Conclusions and policy implications

In this paper, we analyze the inclusiveness and effectiveness of agricultural cooperatives in Rwanda. We find that cooperatives are to some extent exclusive but that they are effective in improving rural incomes and reducing rural poverty. Our findings indicate that there are human capital constraints to participate in cooperatives as farm-households with a more educated household head and more agricultural workers have a higher likelihood to be a cooperative member. Also remoteness is a constraint for cooperative membership. Our results show that, despite these entry constraints, cooperative membership significantly increases farm income (with about 40 to 45%), and significantly reduces the likelihood of being poor (with 10 to 14% points). For a region where about half of the rural population is poor, these are important effects. Our findings support the emphasis of Rwanda on agricultural cooperatives as an institutional vehicle to boost the smallholder farm sector.

Our findings about agricultural cooperatives in Rwanda are similar to findings in the literature on contract-farming, a widely studied institutional innovation. While there is a growing amount of recent evidence that contract-farming has a positive effect on farm performance and farmers' welfare (e.g. Bellemare, 2012; Dedehouanou et al., 2013; Maertens and Swinnen, 2009; Minten et al., 2009; Rao and Qaim, 2011), contract-farming is often found to be exclusive and biased towards better-off or middle-class farmers (e.g. Maertens and Swinnen, 2009; Neven et al., 2009; Rao et al., 2012).

We link the issues of inclusiveness and effectiveness by analyzing the heterogeneity in impact of cooperative membership. We find evidence of a negative selection as the estimated income effect of cooperative membership is largest for farmers with the lowest propensity to be a cooperative member. This negative selection is partially related to the location of farm-households with respect to markets. While farmers in more remote areas have lower propensity the be a cooperative member, the impact cooperative membership has on the income and poverty of more remote farmers is larger. This implies that there is scope for expanding membership of agricultural cooperatives and at the same time improve the effectiveness of cooperatives to raise rural incomes and reduce poverty. This calls for a continued promotion of input and marketing cooperatives in Rwanda, especially in more remote area.

In addition, the observed negative selection is also related to household land ownership. While households who own more land are less likely to be a cooperative member (likely because access to land is a driving force to engage in land cooperatives), the impact of this membership on income and poverty is larger for these households. We find that cooperative membership is not effective in reducing poverty among land-poor households because the impact on their incomes is too low. Contrarily to previous arguments in the literature that cooperatives need to be more inclusive towards the poorest households, our findings indicate that agricultural cooperatives are not a solution for near-landless or land-poor farm-households. Even if cooperative membership marginally increases access to land, the income effect of cooperative membership for these households is too low to get them out of poverty.

We also find that cooperative membership is as effective to improve farm income for more educated farmers as for less educated farmers, as effective for female-headed households as for male-headed household, and as effective for households with many workers as for households with few workers. This calls for making cooperatives more inclusive towards less educated, less experienced and female farmers, and remove human capital constraints for entry into cooperatives – as this would not decrease the effectiveness of cooperatives to improve rural incomes.

Finally, we need to emphasize that our case-study results are specific for the study area in Rwanda. Nevertheless, our results challenge some prevailing judgments about how inclusive agricultural cooperatives are and should be, and about cooperative formation and the impact on rural development and poverty reduction in Rwanda. Our results also underscore the importance of looking beyond average (treatment) effects in studies on the impact of institutional innovation in the agricultural sector, and study impact heterogeneity.

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[i] The national land use policy has played a role in the founding of land cooperatives. Since 2004, the government only allows the cultivation of marshlands, that are considered as a special category of state-owned land, through concessions that are only accessible for officially registered cooperatives (GoR, 2004).

[ii] The original sample size was 401 households but 12 observations were dropped from the analysis because it was unclear whether these observations should be considered as treated or as control observations - the cooperatives they indicate to belong to are unknown by cooperative support organisations and district officials.

[iii] We use the default Gaussian kernel.

[iv] Heterogeneous treatment effects are mostly studied by comparing treatment effects across subsamples with different characteristics (e.g. Ito et al., 2012; Fischer and Qaim, 2012a). Our method, inspired by Abebaw and Haile (2013), Bernard et al. (2008) and Mutuc et al. (2013) has the advantage that non-linearities can be revealed by looking at the whole distribution of the treatment effects.

[v] We restricted this analysis to households with landholdings below 0.85 ha, representing 92% of the sample, in order to capture the behavior of the impact of cooperative membership for smaller (and representative) farms. Full sample analysis did not result in substantial differences but the confidence intervals are very wide at the right hand side of the graphs and the maxima are positioned in the upper deciles of the land variable.

[vi] A ttest for the difference in the estimated ATT on farm income between male- and female-headed households results in a t-value of -0.066 and a corresponding p-value of 0.95. A ttest for the difference in the estimated ATT on poverty between male- and female-headed households results in a t-value of 0.59 and a corresponding p-value of 0.56.