



# Cooperative membership and coffee productivity in Rwanda's specialty coffee sector

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Received: 6 September 2018 / Accepted: 5 July 2019 / Published online: 1 August 2019  
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## Abstract

This study uses data from 1,024 coffee producing households to address two critical questions regarding the role of cooperatives in Rwanda's coffee sector: Does cooperative membership increase adoption of best practices and coffee productivity? and do cooperatives improve farm household welfare? Using a propensity score matching technique to account for selection bias, we find that cooperatives are a critical institution for building farmer capacity, promoting adoption of improved technologies and inputs, and increasing productivity. We discuss the role that cooperatives can play in increasing farmer welfare and reestablishing the coffee sector as a pillar of growth in the country.

**Keywords** Agriculture · Agricultural cooperatives · Farmer organizations · Propensity score matching · Small holder farmers · Specialty coffee

## 1 Introduction

Rwandan coffee is increasingly recognized as a high-quality product, sought after by specialty coffee buyers and consumers world-wide. The coffee sector in Rwanda is made up of over 355,000 farmers, mostly smallholders, and is a major source of export revenue for the country (National Agricultural Export Development Board [NAEB], 2016). Despite impressive growth and a rapid transformation of the sector over the past two decades, coffee productivity in Rwanda, at 385 kg/ha, is among the lowest in East Africa (ICO, 2015). In the late 1990s the Rwandan government began a process of liberalization and privatization of the coffee sector, dismantling barriers to trade, and creating incentives for groups and organizations to invest in coffee production

(Boudreaux 2011). In 2007, the Rwandan government launched the Vision 2020 and the Second Economic Development and Poverty Reduction Strategy (Harrison 2016) both with significant focus on improving the agrarian sector. As part of this, the Crop Intensification Programme (CIP 2007) was designed to increase productivity and to improve food security through agriculture chain integration (Harrison 2016 and Cantore 2011). To this end, CIP created different agencies such as the Rwanda Cooperative Agency (RCA, 2008) and the National Agricultural Export Board (NAEB, 2016). These agencies also created the legal and statutory framework to support the establishment of cooperatives and to contribute to their functioning and proliferation (Ministry of Commerce, Industry, Investment Promotion, Tourism and Cooperatives [MINICOM], 2006; Mujawamariya et al. 2013). Cooperatives in Rwanda have been thought as primordial for the growth of the agrarian sector and to reduce rural poverty; since the creation of RCA the number of cooperatives has increased remarkably with the organization registering nearly 5000 entities (Harrison 2016; Verhofstadt and Maertens 2014). According to Harrison (2016), cooperatives were created to increase entrepreneurship and well-being among farmers. As a result of these programs, the sectors that have experienced significant growth include coffee, maize, and horticulture (Verhofstadt and Maertens 2014).

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The reforms in the coffee sector led to investments in coffee-washing stations (CWS) and incentivized smallholder farmers to shift some production from semi-washed (ordinary) to fully-washed Arabica (specialty<sup>1</sup>) coffee. Consequently, the number of coffee washing stations increased from a single one in 2002 to 245 in 2015 (NAEB, 2016). During this time, farmers also began forming cooperatives, often building their own washing stations to process coffee cherry. The processing sector is comprised of both private and cooperative-owned CWSs. Despite this transformation, the coffee sector in Rwanda continues to struggle with high production costs, low productivity, and low producer cherry prices (Clay et al. 2016). Over the past decade, collective action mechanisms such as farmers getting together voluntarily in agricultural cooperatives – where they can contribute to their governance through participatory decision making and share risks – are being used as a means to overcome some of these challenges (Abebaw and Haile 2013; Ma and Abdulai 2016; Mojo et al. 2016; World Bank 2008). Rwanda's coffee cooperatives are farmer organizations established to improve smallholder income and livelihoods mainly by providing technical assistance and inputs for production, processing fully-washed coffee, increasing farmers' bargaining power and market entry opportunities (Bizoza 2011; OCIR, 2005). Many of these cooperatives have emerged as a result of government and NGO support (Loevinsohn et al. 1994) aiming to improve farmers' income by providing services and inputs for production, to process high quality products and increase farmers' bargaining power (Mujawamariya et al. 2013). Additionally, NGOs and development programs have helped farmers establish cooperatives and have trained members in various aspects of coffee production, processing and marketing. At present, 14% of coffee farmers are members of a cooperative or smallholder association (NAEB, 2016).

Smallholder coffee farmers in Rwanda, like those in other sectors throughout sub-Saharan Africa, face imperfect markets, high transaction costs and marketing constraints. As in other parts of the world, low coffee prices and productivity constraints have also led to financial and social hardships (Chiputwa et al. 2015; Ikeno 2007; Varangis et al. 2003). Collective action through the formation of cooperatives has emerged as a means to overcome some of these constraints. Agricultural cooperatives are seen as important institutions having two broad objectives: a) economic and business development and b) social inclusion and empowerment (Poole and Donovan 2014). Among the economic and business development objectives, augmenting farmer capacity, providing technical assistance, expanding access to markets, obtaining

market information, improving product quality, strengthening farmers' negotiation abilities and reducing transaction costs are very relevant goals (Bernard and Spielman 2009; Hellin et al. 2009; Holloway et al. 2000; Ma and Abdulai 2016; Markelova et al. 2009). Social inclusion and empowerment facilitate the creation of collective capacity and the formation of social and human capital (Poole and de Frece 2010). However, many African countries have a history of failing cooperatives explained in part by their origins under colonial authorities, but also by management problems under government control (Develtere et al. 2008). A new era of cooperatives emerged in Africa in the twenty-first century. These new cooperatives are based on the notion that they are voluntary and should serve to alleviate poverty and encourage community participation. Research on the effects of cooperatives on farm household welfare has found varying levels of success (Attwood and Baviskar 1987; Kodama 2007; Narrod et al. 2009; Neven et al. 2005; Poole and de Frece 2010; Poole and Donovan 2014; Tendler 1983; Uphoff 1993; Verhofstadt and Maertens 2014). Some qualitative studies conducted with cooperatives in Rwanda show that these organizations are increasing inequalities in rural communities (Nabahungu and Visser 2011; Ansoms 2010). Verhofstadt and Maertens (2015) found that cooperatives in Rwanda are exclusive towards the poorest farmers, but they improve rural income and reduce poverty among their members. For the case of cooperatives working with Fair Trade Certification, Elder et al. (2012) found that farmers belonging to a cooperative mistrusted their cooperative board members, but farmers belonging to cooperatives perceived more farmer participation in decision making than farmers belonging to private coffee washing stations. Understanding the effectiveness of cooperatives is important because it extends our knowledge beyond the immediate effects on agronomic practices and marketing efficiencies to whether and how cooperatives can contribute to broader measures of household well-being, including incomes, food security, and nutrition and health outcomes.

This question becomes especially important in the Rwandan context where farms are comparatively 'the smallest' in the global industry averaging 0.10 ha per farm (NAEB, 2016). Thus, some type of organization into larger units can play a particularly valuable role. The viability and future growth of the coffee sector can be greatly improved if CWSs are able to improve technical capacities of farmers, raise their productivity, operate profitably, and create economic, technical and social incentives for more farmers to supply the fully-washed channel rather than processing cherries themselves for the semi-washed market (Boudreaux 2011; Macchiavello 2015). In this study, we address two critical questions regarding the role of cooperatives in Rwanda's coffee sector: Does collective action through cooperative membership increase adoption of best practices and coffee productivity? And, does membership improve farm household

<sup>1</sup> Our use of the term specialty coffee refers to fully-washed Arabica coffee. We note that while all of the specialty coffee comes through the fully washed channel, some lower quality, ordinary coffees are fully washed and never make the specialty grade.

welfare? Utilizing a propensity score matching technique to account for selection bias, we found that cooperatives were a critical institution for building farmer capacity and for promoting adoption of improved technologies and inputs. This has resulted in increased coffee productivity and farmer welfare.

The remainder of the paper is structured as follows. In Section 2, we present additional background on coffee production in Rwanda and the structure of cooperatives in the sector. Our study area and data are described in Section 3 and our empirical framework in Section 4, which discusses how we overcame shortcomings of our methods and the robustness checks used in our analysis. Our results and discussion are presented in Section 5, and conclusions with policy implications derived from our findings in Section 6.

## 2 Background

Agriculture in Rwanda is almost entirely a smallholder system that continues to transition from subsistence to commercial production. Relatively few commercial inputs are used and most labor is manual, with tractors and other mechanized equipment being adopted by only a very small fraction of producers. Coffee, as an export crop, differs from most other crops in Rwanda. Only tea bears some similarity to coffee in that it is a cash crop and is mainly exported, though tea in Rwanda has a very different history and is grown largely on grand scale commercial estates rather than as a crop grown in small quantities by hundreds of thousands of smallholders (Diao et al. 2010). Coffee production in Rwanda has for generations been a primary source of cash income for farmers. It has been complementary to the country's main food and subsistence crops such as bean, sorghum, sweet potato, maize and banana, which are often consumed on farm or traded locally. Coffee income today is generally used by producer households to cover school fees, medical expenses, clothing, household goods and, for many, the purchase of food, particularly during food insecure periods before the harvest season (Clay et al. 2018). Unlike most food crops, coffee is traded internationally and is historically Rwanda's primary source of foreign exchange revenue. For this reason, coffee, along with tea production and sales, has been closely regulated by the national exports board (NAEB).

Coffee cooperatives producing fully-washed Arabica coffee in Rwanda tend to be organized around coffee washing stations. In some cases the cooperatives own and operate the washing stations and in other cases they are organized purely as producer cooperatives, established to supply privately owned washing stations. Not all coffee producers supplying the washing stations are members of the local cooperative; some, because they are not interested in joining and others because they are unable to meet the costs and responsibilities required by the cooperatives. In some cases, the cooperatives

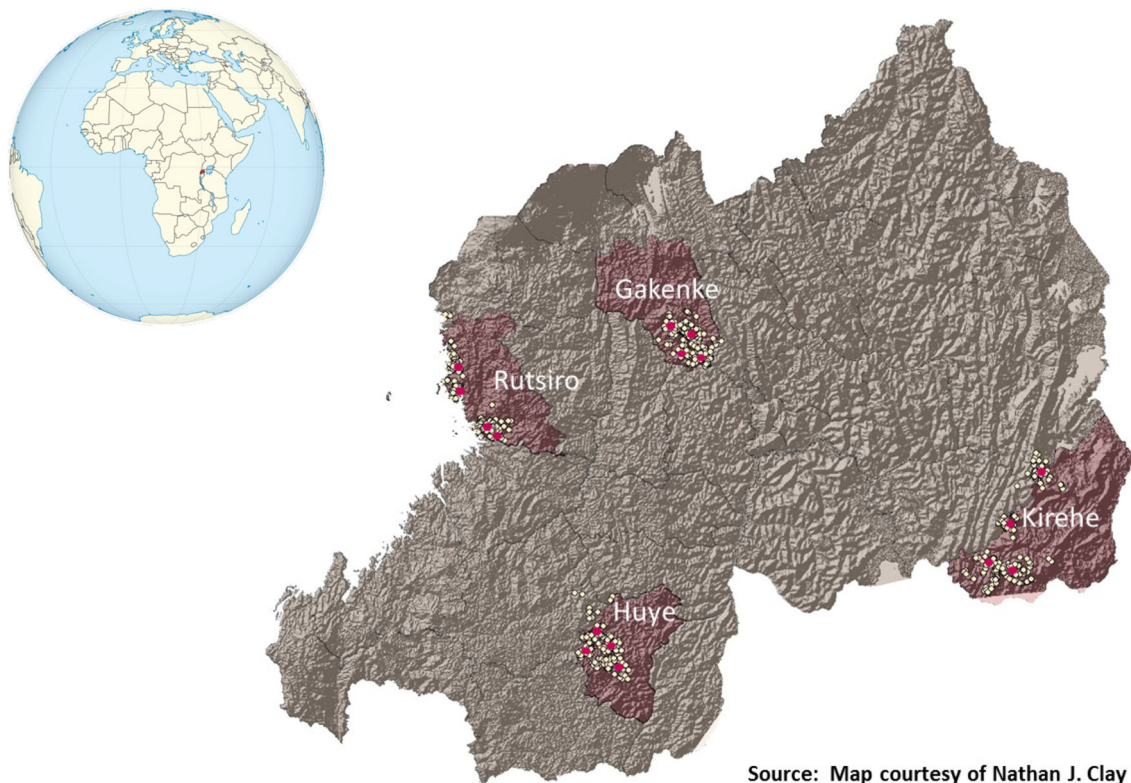
have a minimum coffee tree requirement, but as a rule such minimums are relatively low, in the range of 50–100 trees (Clay et al. 2018). Other potential barriers to membership include a lack of cooperatives' access to certain farmers. The main functions of the coffee cooperatives lie in their regular training and other capacity building services. They also often serve as the node through which government supplied inputs are distributed to members. For cooperatives that primarily supply privately owned washing stations with coffee cherry, their officers frequently serve as the representative of the local producers and are charged with negotiating cherry prices with the private owners.

## 3 Study area and data

A survey of coffee growers in Rwanda was conducted in four major coffee-growing districts representing Rwanda's four agricultural provinces. The selected districts were Rutsiro (Western), Huye (Southern), Kirehe (Eastern), and Gakanke (Northern). From each district, and with the assistance of NAEB staff, four coffee washing stations (CWS) were selected. The guiding objective of CWS selection was to maximize geographic dispersion in each district and also to ensure that the four CWSs would include two that were cooperatively owned and operated and two that were privately owned and operated. From the farmer listings at each of the CWSs, 64 farmers were randomly sampled for study, totaling 1,024 (16 CWS × 64 HH) coffee-producing households (Fig. 1). The sample was designed to be representative of the fully washed coffee sector, which is organized through the country's coffee washing stations. It is important to note that lower quality, "semi-washed" coffees produced in Rwanda are processed on the farm, rather than through washing stations. Thus the sample frame used in this research excludes farmers who only produce coffee for the semi-washed or "ordinary coffee" market.

The survey instruments were developed at the farm household and field levels, and were administered between December 2015 and March 2016 to the head of the household. The questionnaire covered a diversity of topics including: coffee growing practices, cost of production, area under coffee production, number of trees, slope of coffee field, location (GPS), cherry production and sales, landholding, equipment & assets, household income, perceptions barriers to investment in coffee, cooperative membership information and basic household demographics.

Our sample of farmers is comprised of 55% (567) cooperative members and 45% (457) non-members. Summary and descriptive statistics of our sample are presented in Tables 1 and 2. Across our entire sample, 19% of respondents were female heads of households. The average age was 51 years, with 38% reporting at least a primary level of education.



Source: Map courtesy of Nathan J. Clay

**Fig. 1** Map of sampled districts, washing stations and households

Average household size was 5.3 individuals with a dependency score of 0.43 (ratio of the number of individuals under 16 years of age and over 65 years to the total household size). The average respondent household had 24 years of experience growing coffee. Landholdings across our sample were 11,986 square meters at a mean elevation of 1712 m. Approximately 39% of households owned at least 500 coffee trees, with cooperative members having more coffee trees than non-members (Table 2).

Average productivity was reported at 1.75 kg of cherry per tree,<sup>2</sup> with cooperative members having 0.48 kg/tree more than non-members. Coffee income per tree was significantly different between members and non-members at 346.9 and 268.4 Rwandan Francs (RWF), respectively. The average share of income from coffee was 45% across our entire sample. Coffee household's cost of production was calculated by summing all household and wage labor invested in coffee, as well as inputs and equipment costs. Our data show that cooperative members have a significantly lower cost of production at 163.41 RWF/kg compared to non-members at 201.86 RWF/kg. We also constructed an index to capture adoption of best practices. This measure captures whether households

mulched, pruned, applied manure, pesticides, and/or fertilizer on a scale from 1 to 6, where 6 denotes use of all practices discussed. On average, cooperative members reported a higher level of adoption of best practices relative to their non-member counterparts; index of scores of 4.97 and 4.71, respectively.

#### 4 Empirical framework

This study estimates the treatment effect of farmer participation in coffee cooperatives in Rwanda. It assesses the effect of cooperative membership on adoption of best management practices (e.g. fertilizer and pesticide use, pruning and mulching), productivity, income, and cost of production. A major challenge in quantifying the effect of cooperative membership is selection bias, since farmers join cooperatives voluntarily. Cooperative membership is likely correlated with household and farm characteristics such as land holdings or wealth (which may affect farmers' ability to pay cooperative membership fees), education (which may affect farmers' knowledge of the services offered by cooperatives), and experience both with coffee and other cooperatives. Another source of bias in treatment impact estimates lies in the potential endogeneity of access to cooperatives due to non-random placements. Although less of a concern in our context, this

<sup>2</sup> Coffee productivity in Rwanda is reported per tree instead of per unit of land (acre or hectare). Reasons for this include the number of coffee trees that farmers plant per hectare (density) can vary significantly from one farmer to the next, even across fields. Farmers typically have 2–4 coffee fields in different locations, making the area measure more difficult and problematic.

**Table 1** Descriptive statistics

Household characteristics	All Households	Members	Non-Members	Δ
Female HH	19%	21%	16%	6% **
Age HH (years)	51.09 (14.18)	51.34 (13.54)	50.77 (14.93)	0.57
Education HH (primary level)	38%	41%	35%	6% **
Household size (no)	5.33 (2.14)	5.59 (2.15)	5.00 (2.08)	0.59 ***
Dependency	0.43 (0.24)	0.42 (0.23)	0.45 (0.25)	-0.03 *
Experience (years)	24.26 (15.24)	25.44 (15.19)	22.78 (15.18)	2.66 **
Elevation (m)	1711.60 (164.55)	1715.69 (149.04)	1706.53 (182.00)	9.16
Land holding (sqm)	11986.09 (164.55)	13438.12 (11173.35)	10184.55 (9733.33)	3253.57 ***
Huye	0.25	24%	27%	
Rutsiro	0.25	37%	11%	
Kirehe	0.25	23%	28%	
Gakenke	0.25	17%	35%	
Productivity (Kg/tree)	1.75 (1.32)	1.96 (1.45)	1.48 (1.08)	0.48 ***
Coffee Income (RWF/tree)	311.85 (258.2)	346.86 (270.55)	268.42 (235.14)	78.44 ***
Percent of Income from Coffee	0.45 (0.28)	0.49 (0.27)	0.40 (0.28)	0.09 ***
Cost of Production (RWF/Kg)	180.4 (184.8)	163.41 (175.97)	201.86 (193.46)	-38.45 ***
Production Practice Index	4.85 (1.05)	4.97 (0.99)	4.71 (1.09)	0.26 ***

Standard deviations are presented in parenthesis. \*, \*\*, \*\*\* denotes statistical significance at the 0.10, 0.05 and 0.01 levels, respectively. Dependency is the ratio of the number of individuals under 16 years of age and over 65 years to the total household size  
author's data and calculations

type of bias occurs when intentional or implicit policies or regulations favor the creation of cooperatives in specific areas. Because the data were not generated as a random experiment, and cooperative membership assignment is not random, our

**Table 2** Distribution of coffee trees

Number of trees	All Households	Members	Non-Members
≤ 180	18.95%	11.29%	28.45%
181–300	19.53%	19.05%	20.13%
301–500	22.85%	21.34%	24.73%
501–1,000	20.41%	22.93%	17.29%
>1000	18.26%	25.40%	9.41%

author's data and calculations

econometric strategy attempts to control for these identification problems.

Impacts of programs or treatments were evaluated by estimating the average treatment effect on the treated (ATT); that is the outcome of cooperative members, and the outcome of those same cooperative members had they not joined a cooperative:

$$E(W_i|T = 1) = E(Y_i^1|T = 1) - E(Y_i^0|T = 1), \tag{1}$$

where  $W_i$  denotes the unbiased welfare effect for household  $i$  that is treated,  $T = 1$ , or in our case a cooperative member.  $Y_i^1$  is the outcome variable of interest for cooperative members, and  $Y_i^0$  is the outcome variable if the same household were not a member. However, it is impossible to compute this latter

term, because a household belongs to one of two mutually exclusive states, it is either a cooperative member or it is not. Therefore, we can only compare cooperative members and non-members who are not alike:

$$E(W_i|T = 1) = E(Y_i^1|T = 1) - E(Y_i^0|T = 0), \quad (2)$$

where  $E(Y_i^0|T = 0)$ , is the outcome for non-member households. Under random assignment where there is no systematic difference between member and non-member households, eqs. 1 and 2 would lead to identical results. When participating and non-participating households differ in both observable and unobservable characteristics, as is often the case with observational data, equation 2 will lead to biased estimates, with bias  $E(Y_i^0|T = 1) - E(Y_i^0|T = 0)$ .

#### 4.1 Propensity score matching

In order to estimate the effects of cooperative membership, we used propensity score matching (PSM) techniques to match households with similar observable characteristics. A propensity score is the conditional probability that a household has access to the treatment, given observable baseline characteristics. Propensity scores are estimated using a probit model where household characteristics ( $X$ ) are regressed on cooperative membership. These propensity scores,  $P(X)$ , are used to construct an appropriate control group for estimating unbiased ATT:

$$E(W_i|T = 1) = E(Y_i^1|T = 1, P(X)) - E(Y_i^0|T = 0, P(X)).$$

PSM estimates of ATT are based on the assumptions of unconfoundedness and the overlapping condition. The unconfoundedness assumption states that conditional on observable characteristics ( $X$ ), cooperative membership and the potential outcomes are independent:  $(Y_i^1, Y_i^0) \perp T | X$ . The overlapping condition requires that households with similar observable characteristics have a positive probability of being cooperative members and non-members:  $0 < P(T = 1 | X) < 1$ .

We computed two propensity score matching estimators: a single nearest-neighbor matching estimator with replacement, a nearest-neighbor matching estimator using the five nearest neighbors with replacement. Replacement in the nearest neighbor matching increases the quality of the matching by using more information, but it increases the variance of the estimator by reducing the number of non-participant observations used in the comparison group. To ensure robustness, we also performed direct one-to-one covariate matching following Abadie and Imbens 2006 and Imbens 2015.

The propensity scores were estimated using a nonlinear probit regression from a set of observable pretreatment

characteristics (Table 3). The purpose of this regression is to estimate the likelihood or propensity that a household will be a cooperative member. In our specification we included all observable factors from our dataset which could arguably influence membership, in order to create propensity scores which satisfy the balancing property. As noted in the literature (Becker and Ichino 2002; Caliendo 2006; Liverpool-Tasie 2014), the propensity scores were estimated using variables that were not expected to be affected by cooperative membership. These included respondent and household demographic characteristics (sex, age, education, household size), a household dependency measure, the years of experience growing coffee, elevation of the farm (meters), and total household land holdings (square meters). We note that while PSM controls for bias in observable characteristics, it does not necessarily establish a causal relationship between the treatment and outcome variables.

#### 4.2 Sensitivity analysis

Propensity score matching builds on the conditional independence assumption, which means that it only controls for observed heterogeneity between treatment and control groups (Rosenbaum and Rubin 1983). While we use contextual variables to calculate the propensity scores, satisfy the balancing

**Table 3** Probit model results

Variable	Coefficient
Female	0.364 ** (0.112)
Age (years)	-0.005 (0.005)
Education (years)	0.104 ** (0.044)
Household Size (no)	0.049 ** (0.022)
Dependency	-0.400 ** (0.182)
Experience (years)	0.011 *** (0.004)
Elevation (m)	0.002 *** (0.000)
Land (sqm)	6.70E-05 *** 1.06E-05
Land <sup>2</sup> (sqm)	-9.49E-10 *** 2.01E-10
Log Likelihood	-581.08

Constant and district indicators are included in analysis. Standard errors are presented in parenthesis. \*, \*\*, \*\*\* denote statistical significance at the 0.10, 0.05 and 0.01 levels, respectively  
author's data and calculations

property, and utilize observations in the common support, it is still possible that PSM estimates can be biased by some unobserved characteristic that is also driving the treatment effects. To assess the potential effect of hidden bias in our analysis, we calculated Rosenbaum bounds to test the sensitivity of the impact estimates to changes in observable characteristics (Becker and Caliendo 2007; Rosenbaum 2002). Following Rosenbaum (2002), suppose two matched observations with the same observable characteristics differ in their odds of participating solely by the difference in unobserved factors. The Rosenbaum bounds ( $\Gamma$ ) estimate the magnitude that the difference in unobserved factors which drive the participation decision would need to be in order for the estimated effects to be insignificant; with a  $\Gamma = 1$  assuming no hidden bias (indicating that matched households have an equal probability of being a cooperative member) and a  $\Gamma > 1$  denoting various levels of hidden bias.

The Rosenbaum bounds are usually compared to some threshold value that is deemed acceptable. While the propensity score matching literature suggests that a doubling ( $\Gamma = 2$ ) of the level of unobservables is a high threshold given that the estimates are already matched on observable characteristics, we note that the issue of threshold is a delicate and somewhat arbitrary one (Aakvik 2001; Caliendo et al. 2008; Dillon 2011; DiPrete and Gangl 2004). For example, a  $\Gamma = 1.5$  indicates that households that have similar observed characteristics (as captured by the propensity score) could differ in their odds of being a cooperative member by up to 50% due to differences in unobservables (Becker and Caliendo 2007). The robustness of the ATT estimates can be established by identifying the  $\Gamma$  level at which the significance of the relevant bound level falls above 0.10.

## 5 Estimation results and discussion

To estimate the effect of cooperative membership, treatment (member) and control (non-member) households were matched on observable characteristics from the estimated propensity score. We found that the results of the probit estimates guaranteed sufficient overlap in the distribution of the propensity scores between members and non-members with common support given by [0.087, 0.971] with 17 observations outside of it. The covariates used in the specification to generate the propensity scores also satisfied the balancing property (Dehejia and Wahba 2002). That is members and non-members had similar propensity scores within blocks in the region of common support.

We verified that the covariates used in the analysis were balanced and that the differences between adopters and non-adopters had been eliminated (Fig. 2). Table 4 provides a detailed summary of the marginal distributions before and after the nearest neighbor matching procedure. Mean bias

estimates as well as likelihood ratio (LR) test of joint significance of all model covariates before and after matching suggest that our propensity score specifications were generally successful at achieving covariate balance.<sup>3</sup>

To increase the quality of our matches, prior to estimating our ATT, we imposed the common support and trimmed the tails of the distribution by 5% (Smith and Todd 2005). Estimates of ATT from the nearest neighbor PSM estimator suggests that cooperative membership significantly affects adoption of best practices, tree productivity, coffee income, and reduces farmers' cost of production (Table 5).<sup>4</sup> Based on the nearest neighbor PSM estimator, the effect of cooperative membership on adoption of best practices is an increase of 0.497 index points. Coffee cooperatives are known to train farmers on the benefits of adopting best practices and to promote their use among their members. In addition to training, cooperatives distribute inputs such as fertilizers and pesticides, which helps to facilitate adoption of best practices. Adoption of best practices is linked to increases in tree productivity. The nearest neighbor PSM estimator indicates that cooperative members are 20.2% more productive (per tree) than non-members. Although the relationship between crop management and coffee quality has not been studied in detail, good growth conditions (including weed control and pruning) generally have a positive effect on bean size and flavor (Wintgens 2004, Chapter 29). Mulching, for example, promotes water retention and increases nitrogen availability in systems where shade is used to maintain high coffee yields (Youkhana and Idol 2009). An agronomic study in Southwest Rwanda found that mulch and fertilizer application provided synergistic increases in coffee yield (Bucagu et al. 2013). Our findings on productivity are similar to findings in the literature on the effects of cooperative membership (Chagwiza et al. 2016; Ma and Abdulai 2016; Abate et al. 2014).

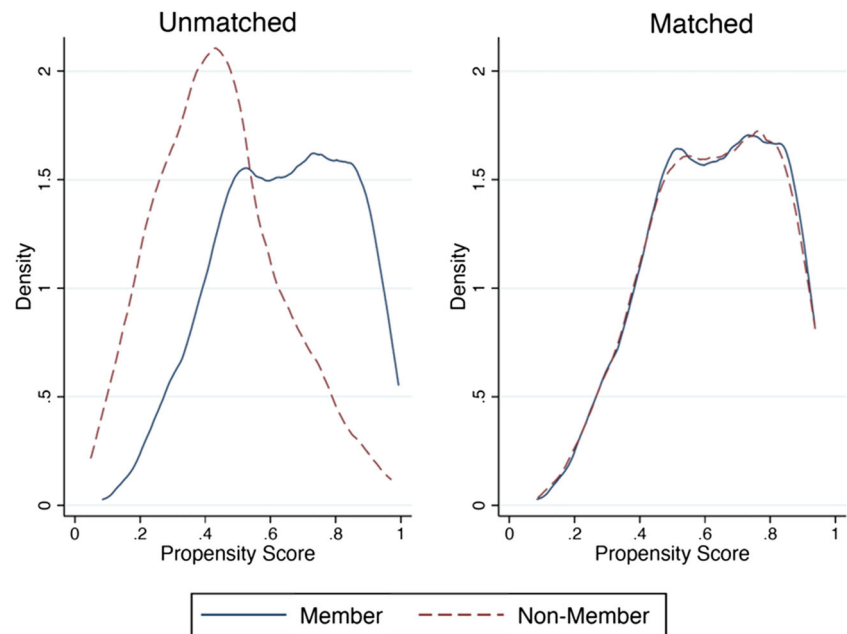
Our analysis finds that cooperative members received 17.8% more income from coffee per tree than non-members. The increase is likely a result of both increased productivity as well as better cherry quality due to adoption of best practices. This result is more conservative than those found by Verhofstadt and Maertens in Rwanda (Verhofstadt and Maertens 2014, 2015) (~43%–56%) and slightly higher than those of Ma and Abdulai (2016) in China (~5%) and is likely due to differences in scope and specification of the outcome variable across studies.<sup>5</sup> Coupled with a 24.1% reduction in the cost of production, we find that cooperative membership

<sup>3</sup> Mean bias before and after matching was 18.9 and 2.9, respectively. *P*-values of LR test before and after matching are <0.01 and 0.99, respectively.

<sup>4</sup> Abadie and Imbens standard errors were calculated for the nearest neighbor PSM matching estimators (Abadie and Imbens 2006, 2016).

<sup>5</sup> The studies by Verhofstadt and Maertens (2015) were conducted in the Muhanga district in the Southern province, mainly on maize and horticulture cooperatives, and the study by Ma and Abdulai was focused on apple production.

**Fig. 2** Propensity score distributions



has a significant effect on net coffee income, or profits. Members' cost of production is significantly lower as some cooperatives provide inputs such as fertilizer and pesticides at lower costs and often assist farmers in their application, reducing labor costs. As a percentage of total income, we find that cooperative members obtain 10.1% more income from coffee than non-members. This finding speaks to the cooperative's role in increasing household incomes and promoting food security. Our results are robust to different matching specifications as shown in Table 5.<sup>6</sup>

Additionally, we conducted an analysis of heterogeneity of impacts by districts (Table 6). While our findings are not driven by any single district, we found some regional variation in our estimates. Cooperatives in Kirehe have the largest effect on farmer adoption of best practices, followed by those in Rutsiro, Gakenke and Huye. Effects on coffee productivity were the highest in Gakenke (37%), followed by Rutsiro (23%). Similarly, decreases in cost of production were seen in Gakenke and Huye district (42% and 23%, respectively). While there was some variation in the size and significance of the treatment effects across the four regions, as noted above, there was a high degree of consistency in the direction of those effects on any given indicator.

As discussed in the previous section, we estimated Rosenbaum bounds to test the robustness of our estimates with regard to hidden bias. These bounds were estimated for the ATT results using the nearest neighbor estimator (Table 7). The values for  $\Gamma$  range between 1.3 and 1.9. The lower bound of 1.3 for coffee income implies that farmers matched with the

same observable characteristics would have to differ in terms of unobservable covariates by a factor of 1.3 or 30%, in order for our estimated ATT to be invalid. The upper bound of 1.9 (best practices) implies that unobserved characteristics would need to differ by 90% in order for our estimate to be invalid. Given that we have already controlled for key observable characteristics between these two groups, we are confident that our estimates are fairly robust to hidden bias.

These results help us to understand how cooperative membership can provide an important pathway to farmers in Rwanda for extracting the most from their plantations and putting the coffee sector on track toward sustainable growth. Rwanda's coffee cooperatives are organized around the principle of supporting members in their adoption of best practices through targeted training in how to mulch, prune, stump and harvest their coffee trees. Moreover, they provide members with greater access to inputs (mainly fertilizers and pesticides), often delivering such inputs directly to the farms at critical times in the growing season. Our results are highly consistent with these goals, showing that cooperative members are indeed more likely to adopt best practices, including the use of improved inputs.

In turn, as we show, the adoption of best practices results in higher yields, with a lower cost of production, making the coffee enterprise for cooperative members more profitable, leading to higher incomes, a prerequisite for longer-term sector sustainability. While not tested in this analysis, we have also learned through case studies with coffee buyers that cooperatives are often seen by buyers of higher quality coffees as a highly desirable source of supply; one they are willing to pay premium prices for. This is because socially-aware consumers in high-end markets in the US and Europe favor single-origin

<sup>6</sup> Results from additional PSM estimators such as Kernel and local linear estimators are available from the authors upon request.



**Table 4** Balancing properties of covariates

Covariate	Unmatched				Matched			
	Members	Non-Members	Diff in means	%Bias	Members	Non-Members	Diff in means	%Bias
Female	0.21	0.16	<b>0.05</b>	13.4	0.21	0.19	0.02	3.3
Age HH (years)	51.34	50.77	0.57	4.0	51.16	51.53	-0.37	-2.6
Education	2.34	2.12	<b>0.22</b>	20.6	2.29	2.25	0.04	2.8
HH size (no.)	5.59	5.00	<b>0.59</b>	28.1	5.49	5.47	0.02	0.5
Dependency	0.42	0.45	-0.03	-10.5	0.42	0.42	0.00	2.1
Experience (years)	25.44	22.78	<b>2.66</b>	16.6	25.15	25.70	-0.55	-3.6
Elevation (m)	1716	1707	9.20	3.3	1715	1709	6.0	3.6
Land (sqm)	13410	10127	<b>3283</b>	31.4	12729	13340	-611	-5.8
Land <sup>2</sup> (sqm)	3.0E+8	2.0E+8	<b>1.0E+8</b>	20.2	2.8E+8	3.0E+8	-0.2E+8	-4.7
Huye	0.24	0.27	-0.03	-6.1	0.25	0.26	-0.01	-2.6
Rutsiro	0.37	0.11	<b>0.26</b>	62.8	0.33	0.32	0.01	2.4
Kirehe	0.23	0.28	<b>-0.05</b>	-9.6	0.24	0.25	-0.01	-1.0

Figures in bold indicate significant difference in means between members and non-members at the 5% level  
author's data and calculations

coffees produced cooperatively by smallholders in low-income countries, especially those with a story to tell. And Rwanda is a nation with a tragic story in its struggle for emotional healing and the need to rebuild its economy in the wake of war and genocide.

## 6 Conclusion and future research

In this paper we analyze the effects of cooperative membership on adoption of best practices, productivity and farm household welfare in Rwanda's fully-washed, specialty coffee sector, using primary data collected in Rwanda in 2016. Because

participation in a cooperative is not random, we used a propensity score matching technique to account for selection bias. Our findings show that cooperatives play a critical role in building farmer capacity, through farmer adoption of improved technologies and inputs, as well as in increasing coffee productivity and farmer welfare. Our analysis finds that cooperative members received more income from coffee per tree than non-members, and faced lower costs of production, which resulted in a significant and a positive effect on profits from coffee.

These results may help to show how cooperatives can contribute to policies which help in the growth and sustainability of Rwanda's coffee sector. Coffee's market potential, agro-ecological attributes (Bro et al. 2017; Perfecto et al., 2007),

**Table 5** Average treatment effects on the treated estimates

	PSM Neighbor (1)	PSM Neighbor (5)	Covariate Matching
Best practice index	0.497 ***	0.480 ***	0.351 ***
st. err.	(0.104)	(0.091)	(0.089)
Log (productivity/tree)	0.202 ***	0.146 ***	0.170 ***
	(0.076)	(0.059)	(0.065)
Log (coffee income/ tree)	0.178 **	0.184 ***	0.146 **
	(0.089)	(0.071)	(0.074)
Percent of income from coffee	0.101 ***	0.094 ***	0.094 ***
	(0.041)	(0.025)	(0.024)
Log (cost of production)	-0.241 ***	-0.224 ***	-0.220 ***
	(0.094)	(0.072)	(0.077)

Abadie and Imbens standard errors are presented in parenthesis for PSM estimators. \*, \*\*, \*\*\* denote statistical significance at the 0.10, 0.05 and 0.01 levels, respectively

authors' data and calculations

**Table 6** Average treatment effects on the treated estimates (nearest neighbor) by district

	Huye	Rutsiro	Kirehe	Gakenke
Best practice index	0.216 (0.160)	0.375 ** (0.183)	0.685 *** (0.174)	0.347 *** (0.136)
Log (productivity/tree)	0.179 (0.111)	0.227 (0.118) *	-0.065 (0.152)	0.373 (0.095) ***
Log (coffee income/ tree)	0.276 ** (0.135)	0.141 (0.134)	-0.093 (0.158)	0.374 *** (0.105)
Percent of income from coffee	0.097 ** (0.046)	0.065 (0.047)	0.142 *** (0.047)	0.051 (0.049)
Log (cost of production)	-0.234 ** (0.111)	-0.106 (0.163)	-0.198 (0.160)	-0.423 *** (0.133)

Abadie and Imbens standard errors are presented in parenthesis. \*, \*\*, \*\*\* denot statistical significance at the 0.10, 0.05 and 0.01 levels, respectively  
author's data and calculations

and contributions to food security (Clay et al. 2016) make a persuasive case for bringing coffee back as a national priority in Rwanda. The results from this study make a compelling argument regarding the role that cooperatives can play in helping farmers overcome high production costs, low productivity, and low producer cherry prices, and in establishing the sector as a pillar of growth in the country.

While past studies have shown that cooperatives in Rwanda may still face barriers associated with poor institutional capacity, such as lack of transparency and lack of inclusiveness, we have, nevertheless, found that cooperatives are effective in helping farmers access improved technologies and generate more income from coffee. This implies that in order to help with the sustainable growth and development of the coffee sector, policies supporting the promotion of cooperative participation among smallholder farmers must provide training that helps to improve the technical and institutional capacity of cooperatives in order to better serve their members.

It is important to emphasize that our analysis focuses on farmer cooperatives operating in the fully-washed Arabic coffee sector. Questions regarding the different forms of agreements between cooperatives and organizations immediately 'down-stream' are also needed. For example, what are the variations in agreements for dry milling (the processing step between the cooperative's product, parchment, and the export product, green coffee)? What are the variations in agreements with licensed exporters, the groups who set export prices and may receive export approval documents from NAEB? Insights on these relationships are important for a better understanding of linkages related to collective action of farmers. Finally, how cooperatives set cherry prices and decide end-of-season premiums and cooperative member 'bonuses' appears to vary greatly. Research in these areas would add important insights on incentives and farmer motivation in the context of cooperative membership.

**Table 7** Rosenbaum bounds sensitivity analysis of PSM ATT estimates to unobserved heterogeneity ( $p$  value for relevant bound)

Gamma ( $\Gamma$ )	Best practice index	Log (productivity/tree)	Log (coffee income/ tree)	Percent of Income from Coffee	Log (cost of production)
1.0	0.000	0.000	0.000	0.000	0.000
1.1	0.000	0.001	0.004	0.000	0.000
1.2	0.000	0.009	0.038	0.000	0.004
1.3	0.000	0.058	<i>0.162</i>	0.001	0.032
1.4	0.000	<i>0.198</i>	0.399	0.009	<i>0.131</i>
1.5	0.001	0.430	0.664	0.043	0.327
1.6	0.004	0.676	0.855	<i>0.139</i>	0.573
1.7	0.017	0.853	0.951	0.307	0.781
1.8	0.052	0.946	0.987	0.519	0.909
1.9	<i>0.127</i>	0.983	0.997	0.715	0.969
2.0	0.246	0.996	0.999	0.856	0.991

Italic numbers correspond to the relevant Gamma at a  $p$  value of 0.10

**Acknowledgements** This research was undertaken by the Feed the Future Africa Great Lakes Region Coffee Support Program (AGLC) as an associate award under the Innovation Lab for Food Security Policy, implemented by Michigan State University and partners. The authors gratefully acknowledge support for this research from the United States Agency for International Development (USAID) Bureau of Food Security. The views expressed in this document do not necessarily reflect those of USAID or the U.S. Government.

The authors wish to acknowledge the contributions of the AGLC public and private sector partners as well as the dedication of the IPAR-Rwanda research and field teams led by Roger Mugisha, Lillian Mutesi, Paul Kayira, and Linda Uwamahoro.

## Compliance with ethical standards

**Conflict of interest** The authors declare that they have no conflict of interest.

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