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Does cooperative membership increase and accelerate agricultural technology adoption? Empirical evidence from Zambia

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ABSTRACT

In developing countries, agricultural cooperatives are increasingly being used to promote improved agricultural technologies and alleviate food insecurity and poverty. However, little is known about the role of agricultural cooperatives in accelerating the adoption of improved agricultural technologies. Using a comprehensive balanced household panel and varietal data, this study applied the difference-in-difference model to identify factors affecting farmers' decision to become cooperative members and the impact of cooperative membership on the adoption of improved maize, inorganic fertilizer and crop rotation. Furthermore, the study used the inverse probability weighted regression adjustment model to analyze the impact of cooperative membership on the speed of adoption of improved maize varieties. We found that cooperative membership increased the probability of technology adoption by 11–24 percentage points. Results further indicated that the average time to adoption was about 8 years, but it was shorter for cooperative members. The results showed that, on average, cooperative membership increased the speed of adoption of improved maize by 1.6–4.3 years. Generally, the results suggest the need for policies which promote farmer organizations such as cooperatives coupled with effective extension services for faster and greater adoption of improved technologies.

1. Introduction

In recent years, cooperatives are increasingly being viewed as a means to promote improved agricultural technologies and alleviate food insecurity and poverty. Cooperative membership tends to increase crop yields, household income, and household assets; and reduce transaction costs in accessing inputs and output markets (Abebaw and Haile, 2013; Ma and Abdulai, 2016; Mojo et al., 2017; Ortmann and King, 2007; Verhofstadt and Maertens, 2015). This is so because in most cases cooperatives are associated with collective action and social capital, hence are thought to be better placed in reducing poverty than other types of institutional innovations (Verhofstadt and Maertens, 2015).

In Zambia, cooperatives have been part of each of the successful political administrations since independence in 1964, with the most common being agricultural cooperatives (Mtonga, 2012). In the early years, cooperatives were largely viewed as a mechanism for stimulating rural development, and not necessarily as institutions for meeting the economic needs of their members (Öjermark and Chabala, 1994). With an estimated number of over 20,379 registered cooperatives in Zambia, the objectives of cooperatives have evolved to better impact and contribute to development such as food production, distribution and support of long-term food security (Mtonga, 2012). With the formation of the Fertilizer Support Programme (FSP)[1] in 2002, cooperatives have become more important because farmers would only access inputs through approved farmer cooperatives or other registered farmer groups. Because maize is the most important staple food in Zambia accounting for about 60% of the calorie intake (Dorosh et al., 2009), it is no surprise that the inputs that were initially considered in the FSP programme were improved maize seed and fertilizer. However, the

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[1] In 2008, this changed to Farmer Input Support Programme (FISP).

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impact of cooperatives on the rate and speed of adoption of agricultural technologies is not well understood in Zambia.

The growing literature suggests that farmer associations increase the adoption of agricultural innovations (Abdulai and Huffman, 2014; Abdulai, 2016; Kabunga et al., 2012; Kassie et al., 2013). However, thorough empirical evidence of the effect of cooperatives on technology adoption using panel data is still lacking. Aside from this, empirical evidence regarding the role of cooperatives in reducing the time to adoption is especially thin. The objective of this paper is to assess the impact of cooperative membership on the rate and speed of improved agricultural technology adoption. The effect of cooperatives on the rate of adoption of improved maize varieties, crop rotation and inorganic fertilizers is analyzed using a balanced household level panel data set and a difference-in-differences *(DID)* method combined with kernel propensity score matching. Similarly, we use a comprehensive varietal and household level data to analyze the effect of cooperative membership on the speed of adoption of improved maize varieties.

The paper contributes to the literature on impact evaluation and duration analysis in the following ways. First, very few studies have used panel data to assess the impact of cooperative membership on technology adoption. We apply a matched *DID* method to analyze the effect of cooperative membership on technology adoption using unique balanced panel data which allows us to control for time-invariant unobserved heterogeneity. Using the *DID* model, we also address the problem of non-random assignment of cooperative membership. Second, to our knowledge, none of the studies so far have used survival treatment effects to examine the effect of cooperative membership on the speed of adoption of improved maize varieties. Specifically, we use the doubly robust inverse probability weighted regression adjustment (IPWRA) model (Wooldridge, 2010) to estimate the impact of cooperatives on the time to adoption. The IPWRA model produces robust and efficient estimates because it enables the researcher to model both the treatment and outcome models. Most previous studies (e.g. Dadi et al., 2004; Abdulai and Huffman, 2005; Nazli and Smale, 2016) used Hazard models to analyze the dynamics of agricultural technology adoption. However, unlike the Hazard models, the results from the IPWRA model are easier to interpret because the effects are in the same time units as the outcome instead of relative conditional probabilities. In addition, the model does not impose additional assumptions of linearity in treatment nor proportional hazards required in Hazard models. Few studies that have used doubly robust estimators in survival analysis include Bai et al. (2013) and Li et al. (2016).

The rest of the paper is organized as follows. In the next section, we present a review of literature on cooperatives and adoption of agricultural technologies followed by the empirical frameworks for the estimation of the impacts of cooperatives on the rate and speed of technology adoption. Section 4 presents the sampling procedure and discusses the descriptive results. The fifth section presents the empirical results, whereas the last section draws conclusions and provides policy recommendations.

2. Literature review

2.1. Factors influencing farmers' participation in agricultural cooperatives

Agricultural cooperative membership is a major force of knowledge and technological transfer, due to not only the spillover effects of the collective use of a technology, but also since collective action facilitates innovation and learning by members of the group (Chagwiza et al., 2016). Previous studies on cooperatives have identified several factors that affect the participation of households in cooperatives (e.g. Abebaw and Haile, 2013; Fischer and Qaim, 2012; Ma et al., 2018a; Ma and Abdulai, 2016; Mojo et al., 2017; Shiferaw et al., 2008; Sitko and Jayne, 2014; Verhofstadt and Maertens, 2015; Wossen et al., 2017). These can be grouped into household and farm factors (e.g. age of the household, sex, education, household size, land and livestock ownership, access to off-farm income, contacts with extension agents); social capital and networking (e.g. number of years in the village, relatives in leadership positions, and kinship); and locational factors (distance to cooperative office).

Several studies have shown that age and education of the household head can affect cooperative membership. Older and more educated farmers are more likely to be members of cooperatives (Chagwiza et al., 2016; Fischer and Qaim, 2012; Wossen et al., 2017). Women in Africa usually have limited opportunities to participate in collective action such as cooperatives, hence male-headed households are more likely to be members of cooperatives than their female counterparts (Abebaw and Haile, 2013). The size of the household usually has a positive effect on the likelihood of cooperative membership and this is partly because of increased household labor endowment (Ma et al., 2018a; Verhofstadt and Maertens, 2015; Zheng et al., 2012).

Land ownership is an important resource for most smallholder farmers and previous studies have shown that it has a positive (sometimes negative) effect on the likelihood of farmers to join agricultural cooperatives. The majority of studies however show that participation in cooperatives increases with land ownership (Ma and Abdulai, 2016; Ma et al., 2018a; Mojo et al., 2017; Wossen et al., 2017). Other studies show a negative relationship between land ownership and the likelihood of cooperative membership (Chagwiza et al., 2016). Livestock ownership is usually a proxy for houshold wealth and this has been shown to increase participation in cooperatives (Verhofstadt and Maertens, 2015; Wossen et al., 2017). The extent to which farmers have access to off-farm income also influences the participation in cooperatives. A study by Abebaw and Haile (2013) shows that off-income increased the probability of participating in cooperatives and this is because off-farm income increases the income security of households.

Farmers who have regular contacts with extension agents are in a better position to gather useful information regarding the benefits of belonging to a cooperative (Abebaw and Haile, 2013). The prevailing evidence also suggests that access to credit matters as well. Farmers who have no liquidity constraints are more likely to join cooperatives (Wossen et al., 2017; Fischer and Qaim, 2012), as they can, for instance, easily pay membership fees. Social networks are expected to increase the likelihood of cooperative membership because these are usually associated with collective action (Abebaw and Haile, 2013; Mojo et al., 2017; Verhofstadt and Maertens, 2015). Finally, the distance to a cooperative office is a proxy for transaction costs and it is expected that the further away the household is from the cooperative office, the less the likelihood that it would be a member of a cooperative.

In the context of developing countries, empirical evidence suggests that cooperative membership is significantly associated with the adoption of agricultural technologies. In Kenya, for instance, Fischer and Qaim (2012) show that cooperative membership increased the adoption and intensity of use of improved bananas. Similarly, cooperative membership was highly correlated with the adoption of several innovations in Nigeria, including improved maize varieties, inorganic fertilizers and pesticides (Kolade and Harpham, 2014). Aside from increasing technology adoption, agricultural cooperative/group membership was also essential in promoting the efficient usage of productive inputs among apple farmers in China and farm performance in the Great Lakes region of Africa (Ainembabazi et al., 2017; Ma et al., 2018b). While these are important studies, most of them are based on cross-sectional data. Empirical evidence on the impact of cooperatives on the speed of technology adoption is especially rare. This study extends previous works on the impact of cooperatives on technology adoption by using a unique and comprehensive panel dataset. Furthermore, we use survival treatment effects as opposed to Hazard models to estimate the impact of participating in cooperatives on the speed of improved maize adoption.

2.2. Factors influencing the adoption of improved agricultural technologies

In the extant adoption literature, there are several empirical studies that have analyzed the factors that affect the adoption of improved agricultural technologies with many of them applying discrete choice models (e.g. Adegbola, 2010; Kassie et al., 2013; Khonje et al., 2015) to identify the relevant factors. In these types of studies, the timing of adoption is not considered. Other studies model technology adoption in a dynamic process where farmers learn about the technology over time and adopt when the expected returns are positive (Alcon et al., 2011). In these time to adoption studies, duration analysis models have been used to examine the determinants of technology or speed of technology adoption (e.g. Abdulai and Huffman, 2005; Beyene and Kassie, 2015; Dadi et al., 2004; Nazli and Smale, 2016). In the subsequent paragraphs, we highlight several factors, gleaned from the literature which are likely to influence the speed of technology adoption.

Earlier studies recognize several factors that are likely to influence the speed of technology adoption, which can be grouped in a similar way as those highlighted in Section 2.1 above (i.e. household and farm factors, social capital and networking and locational factors). Among the household and farm characteristics, education, household size, land and livestock ownership have been shown to increase the speed of technology adoption (Beyene and Kassie, 2015; Dadi et al., 2004; Nazli and Smale, 2016; Euler et al., 2016). Contact with extension agents is generally viewed as a proxy for information access and several studies show that it is vital for technology adoption (e.g. Abdulai and Huffman, 2005; D'Emden et al., 2006). The effect of age on technology adoption is usually indeterminate with some studies showing a negative and others positive effect (Beyene and Kassie, 2015; Nazli and Smale, 2016). This is so because older farmers may have more exposure to production technologies and accumulated substantial wealth, but at the same time, increase in age can also be associated with loss of energy and short-planning horizons, as well as being more risk averse (Adegbola and Gardebroek, 2007; Kassie et al., 2013). Agricultural technology adoption usually comes at a cost (e.g. cost of improved seed and fertilizer), hence for farmers with inadequate accumulated resources, it may be difficult for them to adopt such technologies. Farmers who have access to credit can on the other hand relax their financial constraints (Adegbola and Gardebroek, 2007). Several previous studies have shown that access to credit reduces the time to technology adoption (Alcon et al., 2011; Dadi et al., 2004; Yigezu et al., 2018). Social capital and networks such as years a household has lived in the village and the number of relatives and a friend a household can rely upon (kinship) generally enhance the adoption of agricultural innovations (e.g. Beyene and Kassie, 2015; Kassie et al., 2013). Distance variables are usually proxies of transaction costs in either accessing information or markets, hence are most likely to reduce the uptake of improved agricultural technologies. For instance, Matuschke and Qaim (2008), show that the distance to the input dealer as a source of information increased the time to adoption of hybrid peal millet in India.

3. Empirical procedure

3.1. Impact of cooperative membership on technology adoption

To determine the impact of cooperative membership on technology adoption, we use the *DID* model, combined with kernel propensity score matching to control for both time-invariant unobserved and observed heterogeneity. We compare the technology adoption behavior of cooperative members with non-cooperative members. The *DID* estimator is defined as the difference in average outcome in the treatment group before and after treatment minus the difference in average outcome in the control group before and after treatment. Following Villa (2016) and Khandker et al. (2009a, 2009b), let $t = 0$ denote the baseline period and $t = 1$ the follow-up period. Furthermore, let $I_i = 1$ denote cooperative members and $I_i = 0$, non-members. The treatment indicator at baseline can then be specified as $(D_{it=0} = 0|I_i = 0)$ and $(D_{it=1} = 1|I_i = 1)$ for the follow-up. The *DID* estimator can then be expressed as:

$$DID = \{E(Y_{it=1}|(D_{it=1} = 1, I_i = 1, X_i) - E(Y_{it=1}|(D_{it=1} = 0, I_i = 0, X_i)\} - \{E(Y_{it=0}|(D_{it=0} = 0, I_i = 1, X_i) - E(Y_{it=0}|(D_{it=0} = 0, I_i = 0, X_i)\} \quad (1)$$

where Y_{it} indicates the outcome variables (adoption of improved maize, inorganic fertilizers, and crop rotation); $X_i$is a vector of observed characteristics of cooperative and non-cooperative members. The double differencing in Eq. (1) removes biases in second period comparisons between the treatment and control group that could result from permanent differences between those groups, as well as biases from comparisons over time in the treatment group that could be the result of time trends unrelated to the treatment (Imbens and Wooldridge, 2009). Kernel propensity score weights can be added to Eq. (1) to obtain a kernel propensity score *DID* treatment effect as follows:

$$DID = \{E(Y_{it=1}|(D_{it=1} = 1, I_i = 1) - w_i * E(Y_{it=1}|(D_{it=1} = 0, I_i = 0)\} - \{E(Y_{it=0}|(D_{it=0} = 0, I_i = 1) - w_i * E(Y_{it=0}|(D_{it=0} = 0, I_i = 0)\} \quad (2)$$

where $w_i$denotes the kernel propensity score weights.

The *DID* relies on several assumptions, including the Stable Unit Treatment Value assumption (SUTVA) (Rubin, 1977), exogeneity assumption, and the parallel or common trend assumption. The parallel trend assumption is a strong and most important assumption for the *DID* model and it states that the average change in the outcome variable for the treated in the absence of treatment is equal to the observed average change in the outcome variable for the controls (Mora and Reggio, 2012). The assumption implies that if the treated had not been subjected to the treatment, both sub-populations would have experienced the same time trends conditional on the observed characteristics (X) (Lechner, 2011).

3.2. Impact of cooperative membership on the speed of adoption of improved maize varieties

Duration analysis is important because it helps to identify the factors that explain the length of a spell, where the spell starts at the time when a farmer becomes aware of a technology for the first time, and ends at the time a farmer adopts the technology (Beyene and Kassie, 2015). However, because of the problems with recall data, we define the time to adoption as the difference between the year of adoption and the year of release of a variety (Abdulai and Huffman, 2005; Nazli and Smale, 2016).

Most previous studies (e.g. Abdulai and Huffman, 2005; Beyene and Kassie, 2015; Nazli and Smale, 2016) have used duration analysis models where the probability of non-cooperative membership is reflected by the Hazard rates, which is the core function in duration or survival analysis. One of the shortcomings of Hazard rates is that they are difficult to interpret and therefore difficult to explain to policy makers and other people who may not be familiar with survival analysis. An alternative way to estimate the effect of cooperatives on the time to adoption would be to use the survival treatment effects approach. This method provides estimates that are easy to interpret and understand. Specifically, we use the likelihood-adjusted-censoring IPWRA to estimate the effect of cooperative membership on the time it takes for farmers to adopt improved maize varieties.[2]

The most commonly used methods to estimate treatment effects

[2] We also estimated the Hazard based models as a robustness check.

using non-experimental survival or time to event data include inverse probability weighting (IPW) and propensity score matching (PSM) (Austin, 2011; Austin and Stuart, 2017; Bellemare and Novak, 2017). However, if the propensity score equation is misspecified, then biased estimates may be obtained. To control for this, we use the IPWRA (Li et al., 2016; Wooldridge, 2010). The IPWRA uses the IPW to model the treatment equation and the regression adjustment (RA) to model the outcome equation. If both the treatment and outcome equations are correctly specified, then efficient, robust estimates would be obtained.[3] In estimating the IPWRA model, three steps are followed (StataCorp, 2015). First, we estimate the parameters of a treatment-assignment (propensity score) model and compute inverse probability of treatment weights using IPW. Second, we obtain the treatment specific predicted mean outcomes for each household by using the weighted maximum likelihood estimators. Estimated inverse probability of treatment weights are used to weight the maximum likelihood estimator. A term in the likelihood function adjusts for right-censored survival times. Third, we compute the means of the treatment-specific predicted mean outcomes (i.e., the time to adoption) using the weighted regression adjustment. Differences of these averages provide the estimates of the average treatment effects (ATEs) and if we restrict the computations of the means to the subset of cooperative members, we obtain the average treatment effect on the treated (ATT). In the subsequent paragraphs, we describe the models used to estimate the ATEs and the ATT.

Following Bellemare and Novak (2017) and Wooldridge (2010), assume that the outcome model is represented by a linear regression function of the form:

$$y_i = \alpha_1 + \beta_1 x_i + \delta_1 C_i + \mu_i \tag{3}$$

where $y_i \geq 0$ is the time to adoption, x_i is a set of control variables, C_i indicates whether an individual is a member of a cooperative or not, such that $C = 1$ if a farmer belongs to a cooperative and $C = 0$ if a farmer is not a member of a cooperative; μ_i is the error term. The coefficient on C_i measures the average treatment effect (ATE). The ATE for the IPWRA for observational data as presented in Wooldridge (2010), which can be generalized to observational survival-time data can be represented as:

$$\begin{aligned} ATE_{IPWRA} &= N^{-1}\sum_{i=1}^{N}[(\alpha_1^* + \beta_1^* x_i) - (\alpha_0^* + \beta_0^* x_i)] \\ &= (\alpha_1^* - \alpha_0^*) + \bar{x}(\beta_1^* - \hat{\beta}_0)] \end{aligned} \tag{4}$$

where (α_1^*, β_1^*) are attained from the inverse probability-weighted least squares problem for cooperative and non-cooperative members. The * on the estimated parameters α and β, describes the double robustness result. Restricting our estimation on the subset of cooperative members, we can express the ATT as:

$$\begin{aligned} ATT_{IPWRA} &= N^{-1}\sum_{i=1}^{N}[(\alpha_1^* + \beta_1^* x_i) - (\alpha_0^* + \beta_0^* x_i)] \\ &= (\alpha_1^* - \alpha_0^*) + \bar{x}_1(\beta_1^* - \beta_0^*)] \end{aligned} \tag{5}$$

The technical details regarding the formulas for the estimation procedure for the survival treatment effects (ATE and ATT) can be found in StataCorp, (2015).

Since we use cross-sectional data to estimate the ATE and ATT, for the treatment effects to hold, there are several assumptions that need to be made and these include the conditional independence (CI), enough overlap, and correct adjustment for censoring. Conditional on *x, C* and (y_0, y_1) are independent and this is usually referred to as the conditional independence assumption (Rosenbaum and Rubin, 1983) .[4] This assumption cannot be tested but it has a better chance of holding if the control variables are rich (Wooldridge, 2010). We believe that the covariates included (*x)* are quite rich and will enable us to control for any observed heterogeneity. In estimating the average treatment effects on the treated (ATT), the weaker version of the CI assumption can be invoked which requires only the non-treated potential outcome to be conditionally independent of treatment assignment. The second assumption, i.e. the overlap assumption, states that for any setting of the covariates in the assumed population, there is a chance of seeing units in both the control and treatment groups (Wooldridge, 2010). The overlap assumption rules out the possibility that the propensity score is ever zero or one. We test this assumption in later sections. The third assumption that is usually made with survival analysis data is the correct adjustment for censoring assumption. Part of this assumption entails that censoring time is independent of potential failure time and potential outcomes as well as other confounders conditional on covariates and treatment assignment process (Anstrom and Tsiatis, 2001; Kalbfleisch and Prentice, 2002; Li et al., 2016). Since the IPWRA uses the likelihood-adjusted censoring, this assumption is no more restrictive than assuming correct specification of the outcome model (StataCorp, 2015).

4. Data and descriptive statistics

4.1. Data

The data used in this paper come from two rounds of surveys conducted in 2012 and 2015 in eastern Zambia. The surveys were conducted by the International Institute of Tropical Agriculture (IITA) and the International Maize and Wheat Improvement Center (CIMMYT) in collaboration with the Zambia Agricultural Research Institute (ZARI) for the project entitled Sustainable Intensification of Maize-Legume Systems for the Eastern Province of Zambia (SIMLEZA). The baseline study was conducted in the project districts of Chipata, Katete, and Lundazi which were targeted by the project as the major maize and legume growing areas in eastern Zambia. The districts were first stratified into agricultural blocks (eight in Chipata, five in Katete and five in Lundazi) as primary sampling units. In the second stage, 40 agricultural camps were randomly selected, using probability to size sampling. In total, 17 camps were selected in Chipata, 9 in Katete, and 14 in Lundazi. A total sample of 810 households were selected randomly from the three districts in the first-round and using a questionnaire administered by trained enumerators, data was collected from sampled households through personal interviews. In the follow up survey in 2015, 707 of the same households were interviewed using the same questionnaire used in the baseline survey.

A balanced panel of 707 households was used for the impact analysis on technology adoption, while only 500 observations from the 2015 survey were used for the duration analysis. In the survey, data was collected on and not limited to awareness of improved maize varieties, the year an improved variety was known, sources of varietal information, the varieties grown by the farmers, and year an improved variety was first planted.

4.2. Descriptive statistics

Table 1 shows the definition of variables and summary statistics of the household level variables for the 2012 and 2015 cropping seasons used in the *DID* model. The variables presented in Table 1 were gleaned from the literature presented in Section 2. Improved maize varieties include both hybrid and open pollinated varieties while inorganic fertilizers include D-compound for basal dressing and Urea for top

[3] Note that in non-survival cross sectional data, you only need to correctly specify the treatment or outcome model to obtain doubly robust estimates.

[4] Note that y_0 y_1 denote the time to adoption for non-members and members of a cooperative

Table 1
Descriptive statistics by cooperative membership and survey year.

Variables	Definition	2012 Non-members Mean	Std. Dev.	Members Mean	Std. Dev.	2015 Non-members Mean	Std. Dev.	Members Mean	Std. Dev.
Dependent variables									
Adoption of improved maize	1 = Planted improved maize varieties	0.283	0.452	0.422	0.494	0.277	0.449	0.418	0.494
Fertilizer application	1 = Applied inorganic fertilizer	0.843	0.365	0.962	0.190	0.740	0.439	0.914	0.281
Crop rotation	1 = Practiced crop rotation	0.787	0.410	0.742	0.438	0.727	0.446	0.924	0.265
Independent variables									
Age	Age of the household head (years)	43.016	14.238	43.744	13.287	48.580	15.227	47.116	12.667
Household size	Household size (number)	6.457	2.839	7.166	3.118	7.009	3.324	8.443	4.045
Sex of the household head	1 = Male	0.614	0.488	0.673	0.470	0.719	0.451	0.813	0.390
Education of the household head	Education of the household head (years)	5.634	3.419	6.651	3.367	6.126	3.561	6.363	3.348
Total cultivated land	Total land cultivated (hectares)	2.858	2.149	3.813	3.764	3.314	3.921	4.228	4.851
Livestock ownership	Livestock ownership measured in Tropical Livestock Units (TLU)	2.856	3.521	4.408	4.494	1.823	2.875	3.514	5.732
Contact with government extension	Number of contacts with government extension agents	11.09	23.32	12.472	22.936	0.723	1.371	1.227	2.983
Contact with non-government extension	Number of contacts with non-governmental	11.094	23.319	4.143	11.048	0.394	1.193	0.737	1.653
Extension skills	1 = Trust in the skills of extension agents	4.886	2.158	5.194	2.127	0.740	0.439	0.809	0.394
Years in village	Number of years household head lived in the village	25.772	16.403	27.662	31.075	27.255	15.825	28.101	14.803
Kinship	Number of relatives a household head can rely on for critical support	8.213	19.997	9.949	16.246	3.684	3.604	4.943	5.519
Leadership	1 = Household head has friends or relatives in leadership position	0.555	0.498	0.620	0.486	0.143	0.351	0.214	0.411
Access to off-farm income	1 = Access to off-farm income	0.587	0.493	0.638	0.481	0.455	0.499	0.429	0.495
Access to credit	1 = Access to credit	0.709	0.455	0.786	0.411	0.061	0.239	0.086	0.281
Distance to cooperative	Distance to the cooperative office (minutes)	27.984	41.846	27.874	73.459	49.740	105.262	33.991	89.312
Number of observations		254		453		231		476	

dressing. Results indicate that, overall, the proportions of adopters of improved maize, inorganic fertilizer and crop rotation were higher for members of the cooperative than for non-members in 2012 and 2015. On average, 42% of the cooperative members planted improved maize in 2012 and 2015 while over 90% of the members applied inorganic fertilizers in both years. The adoption of crop rotation was higher in 2015 (92%) as compared to 2012 (74%). On average, participants in cooperatives spent slightly more than 6.6 years in school compared to non-participants (5.6 years) in 2012. Members of cooperatives also cultivated more land in 2015 as compared to 2012. Similarly, cooperative members had more contact with extension agents, access to off-farm income, access to credit and owned more livestock than non-members in 2012 and 2015.

The importance of social capital and networking is well documented in the literature (Isham, 2002; van Rijn et al., 2012; Verhofstadt and Maertens, 2015; Wossen et al., 2015). Social capital and networking play an important role in not only cooperative membership, but also in mitigating against production and income risk. We proxy social capital and networks using kinship, the number of years a farmer has lived in the village and having friends or relatives in leadership positions. The results further show that on average cooperative members had more relatives they could rely upon for critical support than non-members.

Table A1 in the appendix presents the descriptive statistics of the variables used in survival analysis (Section 3.2). The variables are like those in Table 1, the only difference is that Table A1 results are only for the year 2015, defined at varietal level and the sample size is 500, and not 707 as in the *DID* model. The interpretation of the results is like that of Table 1, except for the time to adoption and age of the household head.[5] Results indicate that the average time taken between the time a variety is released and adopted (planted) was 7.6 years. Cooperative members took a shorter time to adopt as compared to non-members and the difference is significant. The time to adoption is relatively larger as compared to other studies done on maize such as that by Beyene and Kassie (2015) and this is probably because of the way we defined our time to adoption. In the case of Beyene and Kassie (2015), the time to adoption was defined as the difference between the year a farmer became aware of an improved variety and the year the variety was adopted. The age at variety adoption is slightly lower (42 years) compared to the age during the surveys (Table 1).

5. Empirical results

5.1. Determinants of cooperative membership

Table 2 presents the probit model estimates of the baseline propensity score matching from the *DID* model.[6] Consistent with previous studies on cooperatives (e.g. Ma et al., 2018a; Verhofstadt and Maertens, 2015; Wossen et al., 2017), we find that households with more educated household heads have a higher probability of being members of a cooperative. The results show that education increases the probability of participating in a cooperative by 1.4%. Similar to Verhofstadt and Maertens (2015), the results also indicate that farmers with more wealth, measured in terms of livestock ownership, were more likely to be members of a cooperative as compared to those with less wealth. This implies that farmers with livestock are 1.6% more likely to be cooperative members than those without.

Farmers who have access to credit are 10% more likely to be members of a cooperative relative to those who have liquidity constraints. This is so because cooperatives may impose costs on poor members in the form of compulsory regular membership fees, hence easing liquidity constraints through credit increases the likelihood of participation in cooperatives (Fischer and Qaim, 2012; Wossen et al., 2017). As expected, transaction costs, represented by the distance to a cooperative office, reduce the propensity of cooperative membership. Specifically, the results indicate that the probability of being a member of a cooperative reduces by about 2.9% given a 10% increase in the time it takes to reach a cooperative office.

[5] Therefore, for the sake brevity, we are not going to interpret all the results in Table 2.

[6] We also estimated a random effects probit and the results are presented in Table A2 in the appendix

Table 2
Determinants of cooperative membership.

Variable	Coefficient	Marginal effects
Age of the household head	0.000 (0.004)	−0.000
Household size	0.019 (0.018)	0.007
Sex of the household head	0.005 (0.109)	0.002
Education of the household head	0.041** (0.016)	0.014**
Total cultivated land	0.018 (0.020)	0.006
Livestock ownership	0.047*** (0.015)	0.016**
Contact with government extension	0.001 (0.002)	0.000
Contact with non-government extension	−0.007* (0.004)	−0.003*
Extension skills	0.042* (0.023)	0.015*
Years in the village	0.003 (0.002)	0.001
Kinship	0.003 (0.003)	0.001
Leadership	0.055 (0.104)	0.019
Access to off-farm income	0.169 (0.105)	0.058
Access to credit	0.289** (0.119)	0.100**
Ln distance to cooperative	−0.083** (0.043)	−0.029*
Katete district	−0.052 (0.132)	−0.018
Lundazi district	0.305** (0.122)	0.106**
Constant	−0.790** (0.310)	
Number of observations	707	

Standard errors in parentheses.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.001$.

5.2. Impact of cooperative membership on technology adoption

Table 3 presents the average treatment effects of cooperative membership. Column 4 in Table 3 shows the average treatment effect on the treated (ATT) for the 2012 survey year, while column 7 is for the 2015 season. The results show that participation in cooperatives increased the probability of adoption of improved maize varieties and inorganic fertilizer. The probability of adoption of improved maize varieties increased by about 13 percentage points due to cooperative membership while the probability of adoption of inorganic fertilizer increased by about 11 percentage points. In 2015, these effects increased to about 18 and 22 percentage points for the adoption of improved maize and inorganic fertilizers, respectively. Even though the effect on crop rotation reduced in 2012, we find that cooperative membership in 2015 increased the probability of crop rotation adoption by 19 percentage points. These results are largely consistent with the findings of Abebaw and Haile (2013), Fischer and Qaim (2012) and Kolade and Harpham (2014). The adoption of improved maize varieties and inorganic fertilizers is crucial for farmers to increase their maize productivity (Khonje et al., 2015; Manda et al., 2016). Crop rotations, especially those that include legumes, also have a number of benefits for both farmers and the environment, including soil improvement through nitrogen-fixation, reduction of diseases, weed and insect populations, and increases in the soil-carbon content, which helps to mitigate the effects of climate change (Andersson et al., 2014; Hutchinson et al., 2007).

The last column of Table 3 presents the matched *DID* estimates representing the ATT differences between the two years. To correct for heteroskedasticity, we use robust standard errors. After controlling for observed and time-invariant unobserved heterogeneity, the results indicate that, overall, the probability of adoption of inorganic fertilizer increased by 11 percentage points with cooperative membership. Similarly, the results reveal that cooperative membership significantly increased the probability of adoption of crop rotation by 24 percentage points. The implication is that cooperatives are not only important in promoting yield-enhancing inputs such inorganic fertilizer but are also essential in fostering the adoption of sustainable intensification practices such as crop rotation.

5.3. Duration analysis

5.3.1. Nonparametric results

A common practice in duration/survival analysis is to first estimate a Kaplan–Meier survival function independent of the explanatory variables. Fig. 1 represents the proportion of the study population still surviving at each successive point in time (Nazli and Smale, 2016). The graph shows that overtime the survival rate falls quickly as the time goes implying that the probability that a farmer will adopt, given that he or she has not adopted previously, seems to increase over time.

To investigate whether a relationship subsists between the time to adoption and cooperative membership, we estimate the Kaplan-Meier survival functions by cooperative membership. Fig. 2 shows that there are differences in the speed of adoption between cooperative members and non-members, with the curve for members having a stepper slope. This implies that cooperative members are more likely to adopt improved maize varieties earlier than non-members. Although these estimates show that there is a relationship between cooperative membership and the speed of adoption of improved maize, this relationship is not causal. To assess any potential causal relationship, we use the parametric models and survival treatment effects.

Table 3.
Impact of cooperative membership on technology adoption (matched *DID*).

Outcome variable	2012 Members	Non-members	ATT	2015 Members	Non-members	ATT	*DID*
Adoption of improved maize	0.419	0.290	0.133 (0.037) ***	0.416	0.232	0.184 (0.049) ***	0.051 (0.061)
Fertilizer application	0.962	0.855	0.107 (0.024) ***	0.914	0.695	0.219 (0.049) ***	0.111 (0.055) **
Crop rotation	0.743	0.790	−0.048 (0.520) ***	0.924	0.737	0.187 (0.047) ***	0.235 (0.057) ***

Robust standard errors in parentheses.
** $p < 0.05$,.
*** $p < 0.001$.

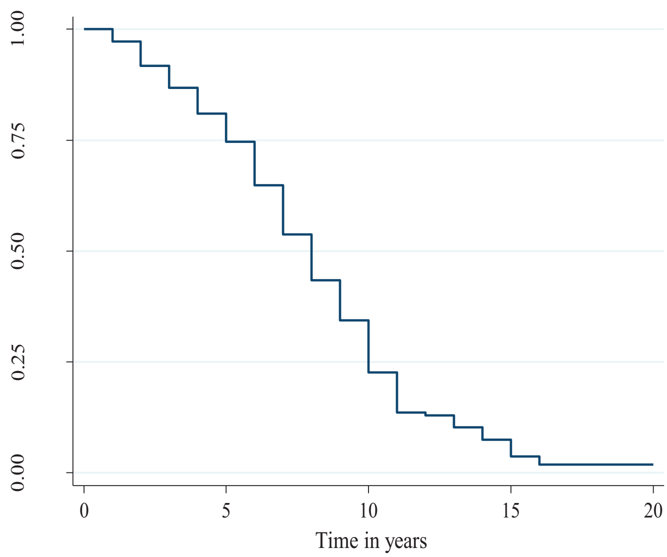

Fig. 1. Baseline time to variety adoption function.

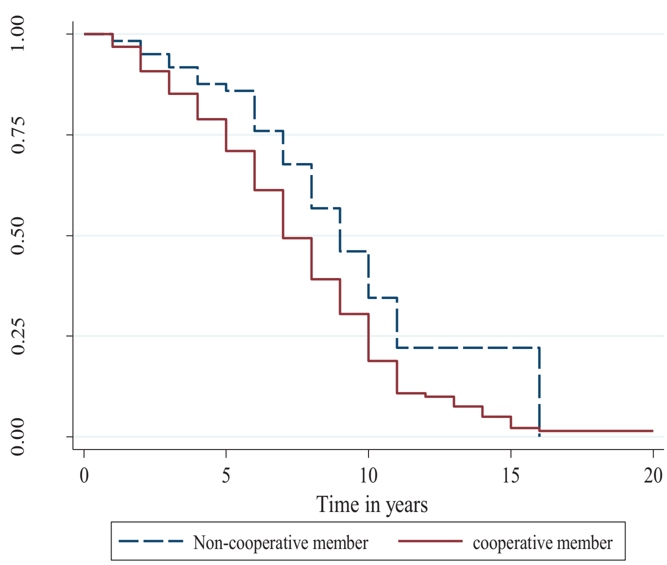

Fig. 2. Baseline time to variety adoption function by cooperative membership.

5.3.2. Parametric results: impact of cooperative membership on the speed of improved maize variety adoption

Table 4 presents the estimates of the IPWRA model specified in Section 3.2. The IPWRA model estimates two separate equations, for cooperative members and non-members. This is important especially if one wants to look at the differential effects of the covariates for the two groups on the time to adoption. There is a variety of functional forms used in the literature and in this paper, we estimate the outcome equations of the IPWRA model using the Weibull and Exponential forms because these are the most commonly used (Dadi et al., 2004). The first stage results are the determinants of cooperative membership from a logit model and the second stage results are the Weibull and Exponential regression estimates on time to adoption. Note that we do not show the results for the determinants of cooperative membership (first stage results) because similar results have been presented in Table 2. Before interpreting the results, we tested the balancing and overlap assumptions. The over identification test for covariate balance (Table 4) shows that we do not reject the null hypothesis that the covariates are balanced, and this implies that the weights constructed from the model balanced the covariates. Since we do not reject the treatment-assignment model, we use the model to assess the overlap condition assumption. Fig. A1 in the appendix indicates that the propensity score distributions for the cooperative members and non-members seem to have the same common support, suggesting that the overlap assumption is not violated.

Since the coefficients have similar signs and significance levels in the two specifications (Weibull and Exponential), we interpret results only for the Weibull model for the sake of brevity. The results for the non-members should be interpreted with caution because of the small sample size (121 observations). Consistent with earlier studies (e.g. Abdulai and Huffman 2005; Beyene and Kassie, 2015; Dadi et al., 2004; Euler et al., 2016), the results show that the time to adoption increases with age for both members and non-members, though it is higher for non-members. Livestock ownership reduces the time to adoption for both cooperative members and non-members. Livestock ownership is an important proxy for wealth; and it is expected that richer households would be in a better position to take possible risks associated with adoption of improved maize varieties and are more likely to purchase inputs, such as fertilizer and improved seeds (Kassie et al., 2013). These results are consistent with Dadi et al. (2004) who found that livestock ownership reduced the time to adoption for teff and wheat in Ethiopia. The results further show that contacts with non-government extension agents reduce the time to adoption. De Souza Filho et al. (1999) found similar results in Brazil where extension services provided by non-governmental organizations significantly increased the speed of adoption of sustainable agricultural technologies. Extension provided by the private sector is generally viewed to be more effective in delivering extension services because they are free from the administrative and political constraints associated with public bureaucracies and is more capable of allocating resources efficiently (Kidd et al., 2000).

The number of years a household has lived in a village increased the speed of adoption only for non-members. The number of years a household has lived in a village is a form of social capital, specifically socio-political capital that could influence how much subsidized fertilizer or improved seed a household receives from the input support programmes (Ricker-Gilbert et al., 2011). Access to off-farm income significantly reduced the time to adoption only for members and this is partly because households that have alternative sources of income may be better able to adopt technologies, since they may have better access to information about new technologies or the capacity to finance investments (Kassie et al., 2013).

The estimates of the impact of cooperative membership on the time to adoption are presented in Table 5. We present both the ATE and ATT for the Weibull and Exponential models. Consistent with the non-parametric results shown in Fig. 2, the results indicate that, on average, cooperative members had a lower time to adoption than non-members. The average treatment effect (ATE), which measures the average effect of cooperatives if all the households were members of the cooperative, indicates that the estimated average time to adoption for all members in the population is 1.5 years less than for non-members for the Weibull model. Put differently, the average time to adoption, if all the households were members of a cooperative, would be 16% less than a situation of non-membership. The Exponential model results show a significant and negative impact of 3.9 years.

In the impact evaluation literature, the ATT is more important with regards to formulating policies. In survival analysis, the ATT is the effect in a well-defined subpopulation which is at-risk, i.e. subpopulation of cooperative members. It is expected that the ATT would be higher than the ATE because households which are likely to benefit the most from cooperative membership are also more likely to choose to be cooperative members. Results from the Weibull model show that, if all households in the subpopulation that are at risk were members of a cooperative, the average time to adoption would be 1.6 years or 17% less than if no household in the subpopulation was a member of a cooperative. Similarly, cooperative membership leads to a 34% (4.3 years) reduction in the time to adoption compared to non-members when we consider the Exponential model. This underscores the

Table 4
Determinants of the speed of adoption of improved maize.

Variable	Time to adoption (Weibull)		Time to adoption (Exponential)	
	Non-members	Members	Non-members	Members
Age of the household head at adoption	0.018**	0.007***	0.029***	0.012***
	(0.006)	(0.002)	(0.008)	(0.003)
Household size	0.013	0.005	0.023	0.010
	(0.016)	(0.006)	(0.028)	(0.009)
Sex of the household head	−0.015	−0.094	0.048	−0.137
	(0.121)	(0.060)	(0.214)	(0.090)
Education of the household head	−0.001	−0.008	−0.002	−0.011
	(0.018)	(0.008)	(0.028)	(0.010)
Total cultivated land	0.011	−0.005	0.014	−0.003
	(0.008)	(0.004)	(0.018)	(0.006)
Livestock ownership	−0.057**	−0.018**	−0.090***	−0.031***
	(0.018)	(0.006)	(0.025)	(0.008)
Contact with government extension	−0.044	0.006*	−0.047	0.008*
	(0.046)	(0.003)	(0.079)	(0.004)
Contact with non-government extension	0.048	−0.054***	0.085	−0.062***
	(0.055)	(0.013)	(0.089)	(0.017)
Extension skills	−0.067	−0.073	−0.129	−0.052
	(0.109)	(0.064)	(0.182)	(0.088)
Years in the village	−0.013***	−0.001	−0.018***	−0.002
	(0.003)	(0.002)	(0.006)	(0.002)
Kinship	0.002	−0.006	0.002	−0.009**
	(0.006)	(0.004)	(0.010)	(0.005)
Leadership	−0.242	0.038	−0.265	0.075
	(0.149)	(0.060)	(0.228)	(0.088)
Access to off-farm income	−0.050	−0.110**	−0.096	−0.146**
	(0.107)	(0.048)	(0.179)	(0.065)
Access to credit	0.301	0.070	0.391	0.041
	(0.200)	(0.100)	(0.376)	(0.131)
Distance to cooperative	0.000	−0.000	0.000	−0.000
	(0.001)	(0.000)	(0.001)	(0.000)
Katete district	−0.050	0.151**	−0.055	0.225**
	(0.150)	(0.064)	(0.251)	(0.089)
Lundazi district	−0.275**	−0.075	−0.478**	−0.076
	(0.110)	(0.055)	(0.189)	(0.075)
Constant	2.118***	2.193***	1.959***	2.008***
	(0.312)	(0.149)	(0.509)	(0.205)
Over identification test for covariate balance	χ^2 (18) = 4.599; $P > \chi^2$ = 0.999			
N	121	379	121	379

Robust standard errors in parentheses.
* $p<0.10$,.
** $p<0.05$,.
*** $p<0.001$.

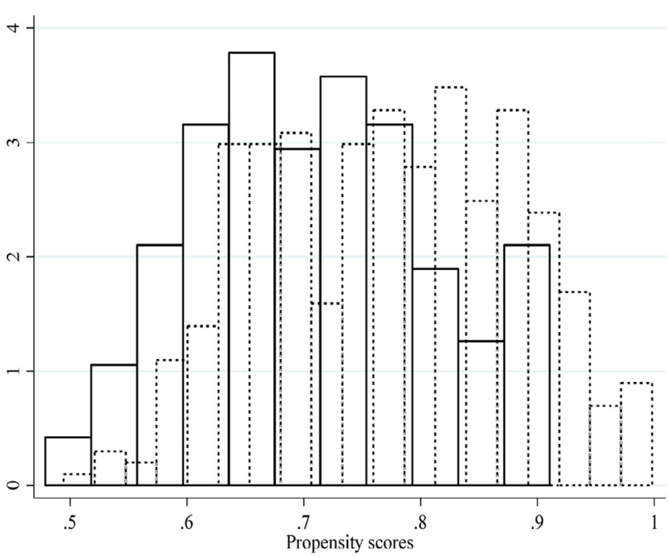

Fig. A1. Propensity scores distribution by cooperative membership.
Note: Dashed lines indicate cooperative members; solid lines indicate non-members.

importance of cooperative membership. In situations where extension agents are not available, farmers can obtain information about improved maize varieties through interactions with other cooperative members. In other words, cooperative membership indicates the intensity of contacts among members (Adegbola and Gardebroek, 2007). As explained earlier, cooperative membership in Zambia is also one of the channels through which farmers' access inputs such as improved maize varieties, hence members may have had access to these inputs earlier than non-members thereby reducing the time to adoption.

As a robustness check for IPWRA model results, we also estimated Eq. (3) using Ordinary Least Squares (OLS) and Hazard models (see Dadi et al., 2004; Euler et al., 2016; Nazli and Smale, 2016 for the modelling procedure of the Hazard models) and the results are presented in Tables A3 and A4 in the appendix. Similar to the IPWRA model, we use the Weibull and Exponential functional forms for the Hazard models. The OLS results are consistent with that of the ATE results presented in Table 5, which indicate that cooperative membership reduces the time to adoption by 0.94 years. Table A3 reports the Hazard ratios with standard errors in parenthesis. A Hazard ratio larger than one implies that the variable speeds up the adoption process; while a Hazard ratio of smaller than one means that the variable slows down adoption (Euler et al., 2016; Nazli and Smale, 2016). Results of the two models are quite similar especially in terms of direction. The results

Table 5
Survival treatment effects on time to adoption.

Outcome variable	Treatment effect	Distribution	Cooperative members	Non-cooperative members	Average treatment effect
Time to adoption	ATE	Weibull	7.620	9.103	−1.483*** (0.489)
Time to adoption	ATT	Weibull	7.632	9.235	−1.603** (0.541)
Time to adoption	ATE	Exponential	8.321	12.244	−3.923** (1.436)
Time to adoption	ATT	Exponential	8.374	12.643	−4.269** (1.624)

Robust standard errors in parentheses,.
** $p<0.05$,.
*** $p<0.001$.

Table A1
Descriptive statistics of the selected variables by cooperative membership.

Variable	Full sample	Members	Non-members	Mean difference
Dependent variable				
Time to adoption	7.634	7.34	8.554	1.213***
	(3.299)	(0.170)	(0.279)	(0.341)
Independent variables				
Age at variety adoption	42.806	42.712	43.099	−0.386
	(13.33)	(0.674)	(1.272)	(1.393)
Household size	8.220	8.475	7.421	1.053**
	(3.958)	(0.211)	(0.303)	(0.411)
Sex of the household head	0.820	0.831	0.785	0.046
	(0.385)	(0.019)	(0.037)	(0.040)
Education of the household head	6.626	6.565	6.818	−0.253
	(3.315)	(0.170)	(0.302)	(0.346)
Total cultivated land	4.223	4.337	3.864	0.473
	(5.094)	(0.262)	(0.456)	(0.531)
Livestock ownership	3.128	3.458	2.092	1.366***
	(4.593)	(0.256)	(0.253)	(0.476)
Contact with government extension	1.166	1.293	0.769	0.524*
	(2.965)	(0.168)	(0.143)	(0.309)
Contact with non-government extension	0.770	0.826	0.595	0.230
	(1.708)	(0.137)	(1.514)	(0.178)
Extension skills	0.784	0.799	0.736	0.064
	(0.412)	(0.020)	(0.040)	(0.042)
Years in village	27.654	28.079	26.322	1.757
	(14.879)	(0.754)	(1.403)	(1.553)
Kinship	4.834	5.142	3.868	1.275**
	(5.534)	(0.301)	(0.378)	(0.575)
Leadership	0.174	0.198	0.099	0.099**
	(0.379)	(0.020)	(0.027)	(0.039)
Off-farm income	0.440	0.427	0.479	0.051
	(0.497)	(0.025)	(0.046)	(0.051)
Access to credit	0.086	0.090	0.074	0.015
	(0.281)	(0.014)	(0.023)	(0.029)
Distance to cooperative	34.251	34.455	33.612	0.844
	(88.975)	(5.054)	(4.481)	(9.300)
N	500	379	121	

Note: Standard deviations in parenthesis for the full sample and standard errors for the members, non-members and mean difference. *.
** , and *** denote significance level at 10, 5, and 1% respectively. The difference is measured by the two-sample *t*-test with equal variances.

Table A2
Maximum likelihood estimates and marginal effects of the random effects probit.

	Cooperative membership Coefficient	Marginal effects
Age of the household head	−0.002	−0.001
	(0.003)	(0.001)
Household size	0.043***	0.015***
	(0.012)	(0.004)
Sex of the household head	0.162*	0.056**
	(0.083)	(0.028)
Education of the household head	0.021*	0.007*
	(0.012)	(0.004)
Total cultivated land	0.008	0.003
	(0.014)	(0.005)
TLU	0.046***	0.016***
	(0.011)	(0.004)
Contact with government extension	0.001	0.000
	(0.002)	(0.001)
Contact with non-government extension	−0.006	−0.002
	(0.004)	(0.001)
Extension skills	−0.014	−0.005
	(0.019)	(0.007)
Years in the village	0.002	0.001
	(0.002)	(0.001)
Kinship	0.003	0.001
	(0.004)	(0.001)
Leadership	0.092	0.032
	(0.086)	(0.03)
Access to off-farm income	0.024	0.008
	(0.078)	(0.027)
Access to credit	0.061	0.021
	(0.094)	(0.032)
Ln distance to cooperative	−0.112***	−0.039***
	(0.031)	(0.011)
Katete	0.107	0.037
	(0.103)	(0.035)
Lundazi	0.184**	0.063**
	(0.089)	(0.031)
Constant	−0.092	
	(0.224)	
chi2	80.768***	
N	1414	

Standard errors in parentheses.
* $p<0.10$,.
** $p<0.05$,.
*** $p<0.001$.

show that cooperative membership increases the Hazard rate by 54% for the Weibull distribution and 36% for the Exponential distribution. The OLS and Hazard model results lend credence to the IPWRA results.

6. Conclusion and policy implications

This paper applies a combination of the matched difference-in-differences and survival treatment effects models to household panel and varietal level data to examine the impact of cooperative membership on technology adoption and the speed of adoption of improved maize varieties in Zambia.

The results from the matched difference-in-differences model suggest that cooperative membership increases the adoption of inorganic fertilizers and crop rotation by 11 and 24 percentage points, respectively. Furthermore, the results indicate that education, livestock ownership, and access to credit were the important determinants of cooperative membership. The results from the doubly robust inverse probability weighted regression model show that, on average,

Table A3
OLS estimates of adoption of improved maize varieties in Zambia.

Variable	OLS
Cooperative membership	−0.944**
	(0.320)
Age at adoption	0.055***
	(0.011)
Household size	0.027
	(0.037)
Sex of the household head	−0.273
	(0.375)
Education of the household head	−0.049
	(0.045)
Total cultivated land	−0.004
	(0.034)
Livestock ownership	−0.157***
	(0.035)
Contact with government extension	0.042
	(0.040)
Contact with non-government extension	−0.246**
	(0.079)
Extension skills	−0.603
	(0.375)
Years in the village	−0.032**
	(0.010)
Kinship	−0.029
	(0.023)
Leadership	−0.291
	(0.372)
Access to off-farm income	−0.480*
	(0.280)
Access to credit	0.657
	(0.553)
Distance to cooperative	−0.001
	(0.001)
Katete district	1.267**
	(0.397)
Lundazi district	−0.172
	(0.324)
N	500

Standard errors in parentheses.
* $p < 0.10$,.
** $p < 0.05$,.
*** $p < 0.001$.

Table A4
Hazard model estimates of adoption of improved maize varieties.

Variable	Weibull	Exponential
Cooperative membership	1.540***	1.359**
	(0.190)	(0.165)
Age at adoption	0.982***	0.987**
	(0.004)	(0.004)
Household size	0.985	0.988
	(0.014)	(0.014)
Sex of the household head	1.141	1.065
	(0.152)	(0.140)
Education of the household head	1.024	1.014
	(0.017)	(0.016)
Total cultivated land	1.002	1.000
	(0.010)	(0.010)
Livestock ownership	1.049***	1.034**
	(0.012)	(0.012)
Contact with government extension	0.986	0.992
	(0.015)	(0.016)
Contact with non-government extension	1.095**	1.046
	(0.034)	(0.032)
Extension skills	1.246*	1.095
	(0.154)	(0.134)
Years in the village	1.006	1.004
	(0.004)	(0.004)
Kinship	1.014	1.007
	(0.009)	(0.009)
Leadership	0.969	0.951
	(0.130)	(0.127)
Access to off-farm income	1.172	1.102
	(0.118)	(0.110)
Access to credit	0.784	0.901
	(0.142)	(0.161)
Distance to cooperative	1.000	1.000
	(0.001)	(0.001)
Katete district	0.680**	0.782*
	(0.095)	(0.107)
Lundazi district	1.217*	1.091
	(0.141)	(0.126)
N	500	500

Standard errors in parentheses.
* $p < 0.10$,.
** $p < 0.05$,.
*** $p < 0.001$.

cooperative membership reduced the time to adoption by up to 4.3 years among cooperative members. Contacts with extension agents, livestock ownership, the number of years the household head lived in the village, and access to off-farm employment were important determinants of the speed of adoption of improved maize varieties. The fact that some of these socio-economic factors had a differential effect on the time to adoption depending on whether or not a farmer was a member of a cooperative suggests that to have an in-depth understanding of what affects the diffusion of improved maize varieties in Zambia, it is vital to consider analyzing such data separately for members and non-members. This can enable policy makers to formulate policies that are tailored to each group or population.

Our results point to the need for policies and strategies that promote and strengthen farmer associations such as cooperatives. With the multiple roles that cooperatives play such as marketing, input distribution, credit and information provision, especially in the presence of market failures (Beyene and Kassie, 2015), the promotion of cooperatives for collective action among smallholder farmers would greatly ease these constraints in addition to reducing the time to adoption of improved agricultural technologies such as yield-enhancing improved varieties, inorganic fertilizers and crop rotation. The results suggest that as cooperatives may impose costs on poor members through obligatory membership fees, easing farmer liquidity constraints through credit provision to poor farmers may greatly increase farmer participation in cooperatives. The significance of contacts with extension agents in reducing the time to adoption indicates the importance of providing farmers with information on the benefits of improved maize varieties. Considering the constraints that the public institutions face with regards to extension provision, the government should create an enabling environment in which the private sector can contribute and fill the void left by government extension in the dissemination of extension messages regarding improved agricultural technologies such as improved maize varieties.

CRediT authorship contribution statement

Julius Manda: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Supervision, Validation, Writing - review & editing. **Makaiko G. Khonje:** Data curation, Investigation, Methodology, Writing - original draft, Writing - review & editing. **Arega D. Alene:** Conceptualization, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Supervision, Validation, Writing - original draft. **Adane H Tufa:** Conceptualization, Methodology, Software, Writing - original draft, Writing - review & editing. **Tahirou Abdoulaye:** Formal analysis, Validation, Writing - review & editing. **Munyaradzi Mutenje:** Data curation, Investigation, Supervision, Writing - review & editing. **Peter Setimela:** Data curation, Funding acquisition, Project administration, Writing - review & editing. **Victor Manyong:** Supervision, Validation, Writing - review & editing.

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Supplementary materials

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References

Abdulai, A., Huffman, W.E., 2005. The diffusion of new agricultural technologies: the case of crossbred-cow technology in Tanzania. Am. J. Agric. Econ. 87, 645–659.
Abdulai, A.N., 2016. Impact of conservation agriculture technology on household welfare in Zambia. Agric. Econ. 47, 729–741.
Abdulai, A., Huffman, W., 2014. The adoption and impact of soil and water conservation technology: an endogenous switching regression application. Land Econ 90, 26–43.
Abebaw, D., Haile, M.G., 2013. The impact of cooperatives on agricultural technology adoption: empirical evidence from Ethiopia. Food Policy 38, 82–91.
Adegbola, P., Gardebroek, C., 2007. The effect of information sources on technology adoption and modification decisions. Agric. Econ. 37, 55–65.
Adegbola, P.Y., 2010. Economic Analyses of Maize Storage Innovations in Southern Benin.
Ainembabazi, J.H., van Asten, P., Vanlauwe, B., Ouma, E., Blomme, G., Birachi, E.A., Nguezet, P.M.D., Mignouna, D.B., Manyong, V.M., 2017. Improving the speed of adoption of agricultural technologies and farm performance through farmer groups: evidence from the Great Lakes region of Africa. Agric. Econ. 48, 241–259.
Alcon, F., de Miguel, M.D., Burton, M., 2011. Duration analysis of adoption of drip irrigation technology in southeastern Spain. Technol. Forecast. Soc. Change 78, 991–1001. https://doi.org/10.1016/j.techfore.2011.02.001.
Andersson, G.K.S., Ekroos, J., Stjernman, M., Rundlof, M., Smith, H.G., 2014. Effects of farming intensity, crop rotation and landscape heterogeneity on field bean pollination. Agric. Ecosyst. Environ. 184, 145–148.
Anstrom, K.J., Tsiatis, A.A., 2001. Utilizing propensity scores to estimate causal treatment effects with censored time-lagged data. Biometrics 57, 1207–1218.
Austin, P.C., 2011. An introduction to propensity score methods for reducing the effects of confounding in observational studies. Multivar. Behav. Res. 46, 399–424.
Austin, P.C., Stuart, E.A., 2017. The performance of inverse probability of treatment weighting and full matching on the propensity score in the presence of model misspecification when estimating the effect of treatment on survival outcomes. Stat. Methods Med. Res. 26, 1654–1670.
Bai, X., Tsiatis, A.A., O'Brien, S.M., 2013. Doubly-robust estimators of treatment-specific survival distributions in observational studies with stratified sampling. Biometrics 69, 830–839.
Bellemare, M.F., Novak, L., 2017. Contract farming and food security. Am. J. Agric. Econ. 99, 357–378.
Beyene, A.D., Kassie, M., 2015. Speed of adoption of improved maize varieties in Tanzania: an application of duration analysis. Technol. Forecast. Soc. Change 96, 298–307. https://doi.org/10.1016/j.techfore.2015.04.007.
Chagwiza, C., Muradian, R., Ruben, R., 2016. Cooperative membership and dairy performance among smallholders in Ethiopia. Food Policy 59, 165–173.
D'Emden, F.H., Llewellyn, R.S., Burton, M.P., 2006. Adoption of conservation tillage in Australian cropping regions: an application of duration analysis. Technol. Forecast. Soc. Change 73, 630–647. https://doi.org/10.1016/j.techfore.2005.07.003.
Dadi, L., Burton, M., Ozanne, A., 2004. Duration analysis of technological adoption in Ethiopian agriculture. J. Agric. Econ. 55, 613–631.
De Souza Filho, H.M., Young, T., Burton, M.P., 1999. Factors influencing the adoption of sustainable agricultural technologies: evidence from the State of Espírito Santo, Brazil. Technol. Forecast. Soc. Change 60, 97–112.
Dorosh, P.A., Dradri, S., Haggblade, S., 2009. Regional trade, government policy and food security: recent evi- dence from Zambia. Food Policy 34, 350–366.
Euler, M., Schwarze, S., Siregar, H., Qaim, M., 2016. Oil palm expansion among smallholder farmers in Sumatra, Indonesia. J. Agric. Econ. https://doi.org/10.1111/1477-9552.12163.
Fischer, E., Qaim, M., 2012. Linking smallholders to markets: determinants and impacts of farmer collective action in Kenya. World Dev. 40, 1255–1268.
Hutchinson, J.J., Campbell, C.A., Desjardins, R.L., 2007. Some perspectives on carbon seques- tration in agriculture. Agric. For. Meterol. 142, 288–302.
Imbens, G.W., Wooldridge, J.M., 2009. Recent developments in the econometrics of program evaluation. J. Econ. Lit. 47, 5–86. https://doi.org/10.1257/jel.47.1.5.
Isham, J., 2002. The effect of social capital on fertilizer use. J. Afr. Econ. 11, 39–60.
Kabunga, N.S., Dubois, T., Qaim, M., 2012. Yield effects of tissue culture bananas in Kenya: accounting for selection bias and the role of complementary inputs. J. Agric. Econ. 63, 444–464.
Kalbfleisch, J.D., Prentice, R.L., 2002. The Statistical Analysis of Failure Time Data. John Wiley Sons, New York, pp. 462.
Kassie, M., Jaleta, M., Shiferaw, B., Mmbando, F., Mekuria, M., 2013. Adoption of interrelated sustainable agricultural practices in smallholder systems: evidence from rural Tanzania. Technol. Forecast. Soc. Change 80, 525–540. https://doi.org/10.1016/j.techfore.2012.08.007.
Khandker, S.R., Bakht, Z., Koolwal, G.B., 2009a. The poverty impact of rural roads: evidence from Bangladesh. Econ. Dev. Cult. Change 57, 685–722.
Khandker, S.R., Koolwal, G.B., Samad, H.A., 2009b. Handbook on Impact Evaluation: Quantitative Methods and Practices. World Bank Publications.
Khonje, M., Manda, J., Alene, A.D., Kassie, M., 2015. Analysis of adoption and impacts of improved maize varieties in eastern Zambia. World Dev. 66, 695–706. https://doi.org/10.1016/j.worlddev.2014.09.008.
Kidd, A.D., Lamers, J.P.A., Ficarelli, P.P., Hoffmann, V., 2000. Privatising agricultural extension: caveat emptor. J. Rural Stud. 16, 95–102.
Kolade, O., Harpham, T., 2014. Impact of cooperative membership on farmers' uptake of technological innovations in Southwest Nigeria. Dev. Stud. Res. 1, 340–353.
Lechner, M., 2011. The estimation of causal effects by difference-in-difference methods. Found. Trends Econ. 4, 165–224.
Li, J., Handorf, E., Bekelman, J., Mitra, N., 2016. Propensity score and doubly robust methods for estimating the effect of treatment on censored cost. Stat. Med. 35, 1985–1999.
Ma, W., Abdulai, A., 2016. Does cooperative membership improve household welfare? Evidence from apple farmers in China. Food Policy 58, 94–102.
Ma, W., Abdulai, A., Goetz, R., 2018a. Agricultural cooperatives and investment in organic soil amendments and chemical fertilizer in China. Am. J. Agric. Econ. 100, 502–520.
Ma, W., Renwick, A., Yuan, P., Ratna, N., 2018b. Agricultural cooperative membership and technical efficiency of apple farmers in China: an analysis accounting for selectivity bias. Food Policy 81, 122–132.
Manda, J., Alene, A.D., Gardebroek, C., Kassie, M., Tembo, G., 2016. Adoption and impacts of sustainable agricultural practices on maize yields and incomes: evidence from rural Zambia. J. Agric. Econ. 67, 130–153.
Matuschke, I., Qaim, M., 2008. Seed market privatisation and farmers' access to crop technologies: the case of hybrid pearl millet adoption in India. J. Agric. Econ. 59, 498–515. https://doi.org/10.1111/j.1477-9552.2008.00159.x.
Mojo, D., Fischer, C., Degefa, T., 2017. The determinants and economic impacts of membership in coffee farmer cooperatives: recent evidence from rural Ethiopia. J. Rural Stud. 50, 84–94.
Mora, R., Reggio, I., 2012. Treatment Effect Identification Using Alternative Parallel Assumptions. Universidad Carlos III de Madrid Working Paper 12-33.
Mtonga, E.M., 2012. Cooperatives and Market Access in Zambia (Discussion Paper).
Nazli, H., Smale, M., 2016. Dynamics of variety change on wheat farms in Pakistan: a duration analysis. Food Policy 59, 24–33. https://doi.org/10.1016/j.foodpol.2015.12.009.
Öjermark, P., Chabala, C., 1994. The Development of Independent Cooperatives in Zambia: A Case-Study. Food & Agriculture Org.
Ortmann, G.F., King, R.P., 2007. Agricultural cooperatives: history, theory and problems. Agrekon 46, 18–46.
Ricker-Gilbert, J., Jayne, T.S., Chirwa, E., 2011. Subsidies and crowding out: a double-hurdle model of fertilizer demand in Malawi. Am. J. Agric. Econ. 93, 26–42.
Rosenbaum, P.R., Rubin, D.B., 1983. The central role of the propensity score in observational studies for causal effects. Biometrika 70, 41–55.
Rubin, D.B., 1977. Assignment to treatment group on the basis of a covariate. J. Educ. Stat. 2, 1–26.
Shiferaw, B., Obare, G., Muricho, G., 2008. Rural market imperfections and the role of institutions in collective action to improve markets for the poor. Nat. Resour. Forum 32, 25–38.
Sitko, N.J., Jayne, T.S., 2014. Exploitative briefcase businessmen, parasites, and other myths and legends : assembly traders and the performance of maize markets in Eastern and Southern Africa. World Dev. 54, 56–67.
StataCorp, 2015. Stata Statistical Software: Release 14. StataCorp LP, College Station, TX.
van Rijn, F., Bulte, E., Adekunle, A., 2012. Social capital and agricultural innovation in Sub-Saharan Africa. Agric. Syst 108, 112–122.
Verhofstadt, E., Maertens, M., 2015. Can agricultural cooperatives reduce poverty? Heterogeneous impact of cooperative membership on farmers' welfare in Rwanda. Appl. Econ. Perspect. Policy 37, 86–106.
Villa, J.M., 2016. diff: simplifying the estimation of difference-in-differences treatment effects. Stat. J. 16, 52–71.
Wooldridge, J.M., 2010. Econometric Analysis of Cross Section and Panel Data. MIT Press.
Wossen, T., Abdoulaye, T., Alene, A., Haile, M.G., Feleke, S., Olanrewaju, A., Manyong, V., 2017. Impacts of extension access and cooperative membership on technology adoption and household welfare. J. Rural Stud. 54, 223–233.
Wossen, T., Berger, T., Di Falco, S, 2015. Social capital, risk preference and adoption of improved farm land management practices in Ethiopia. Agric. Econ. 46, 81–97.
Yigezu, Y.A., Mugera, A., El-Shater, T., Aw-Hassan, A., Piggin, C., Haddad, A., Khalil, Y., Loss, S., 2018. Enhancing adoption of agricultural technologies requiring high initial investment among smallholders. Technol. Forecast. Soc. Change 134, 199–206. https://doi.org/10.1016/j.techfore.2018.06.006.
Zheng, S., Wang, Z., Awokuse, T.O., 2012. Determinants of producers' participation in agricultural cooperatives: evidence from Northern China. Appl. Econ. Perspect. Policy 34, 167–186.

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