Improving the adoption of agricultural technologies and farm performance through farmer groups: Evidence from the Great Lakes Region of Africa

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Abstract

This article examines the effect of membership in farmer groups (MFG) on the adoption lag of agricultural technologies and farm performance in the Democratic Republic of Congo, Burundi and Rwanda. We use duration and stochastic production frontier models on farm household data. We find that long period of MFG reduces adoption lag and much more so if combined with sustainable extension service delivery from government or development agencies. Farmer groups function as an important mechanism for improving farm productivity through reduced technical inefficiency in input use. We discuss the policy implications under which farmer groups are a useful channel to reduce adoption lag, and by what means improved farm performance can be achieved.

1. Introduction

A number of development agencies, research institutions and government programs are increasingly targeting farmer groups as an appropriate channel to achieve successful dissemination and adoption of agricultural technologies (Bernard and Spielman, 2009).[1] This is because farmer groups can internalize transaction costs, facilitate efficient information flow, and reduce both farmers' risk aversion toward new technologies and income shocks through collective risk management (Pingali *et al*., 2005; Hogeland, 2006; Shiferaw *et al*., 2011). To date, however, we still know little about the role of membership in farmer groups (MFG) in reducing the waiting time to adopt agricultural technologies. Yet understanding this role has policy implications, particularly, for agricultural technology change agents seeking to influence farmers' decisions to adopt technologies through farmer groups. This paper examines the role MFG plays in reducing farmers' waiting time to adopt agricultural technologies, and improve farm performance.

There is large body of literature on adoption behaviour of agricultural technologies and the factors explaining the variation in this behaviour (Feder *et al*., 1985; Doss, 2006), but not the delay in adoption. For the case of MFG, this literature is mixed: some studies show that MFG enhances adoption of agricultural technologies (Kristjanson *et al*., 2005; Wollni *et al*., 2010; Kassie *et al*., 2011; Fischer and Qaim, 2012; Abebaw and Haile, 2013), and others indicate otherwise (Herath and Takeya, 2003; Nkamleu and Manyong, 2005; Wendland and Sills, 2008; Alene and Manyong, 2007; Shiferaw *et al*., 2009; Abebaw and Haile, 2013).

In contrast to the voluminous literature explaining the relationship between adoption and MFG, the literature investigating the effect of MFG on farm performance remains scanty and mixed, and has used two different analytical approaches. First, MFG has been considered as an input in the production function in which farmers are assumed to utilize their inputs well and thus are technically efficient, and the effect of MFG on farm performance is determined directly through its marginal product (Dinar *et al*., 2007). For example, Pender and Gebremedhin (2007) find that in Ethiopia, all else fixed, being a member of marketing cooperative would increase crop yields by 44%, but a similar percentage decrease in yields would be observed if a farmer was a member of a farmers' group. Second, MFG has been used, among other covariates, as a

[1] In this study, the term farmer groups is used to refer to both informal and formal farmer cooperatives and associations.

determinant to explain the variation in technical efficiency across farms, and its effect on farm performance is measured indirectly through a change in output due to a change in technical efficiency. Available literature shows that MFG significantly improved technical efficiency in crop production in Ethiopia (Abate *et al*., 2013), while it had ambiguous effects on technical efficiency in Costa Rica: MFG increased technical efficiency among conventional coffee farmers, but not specialty coffee farmers (Wollni and Brümmer, 2012).

This paper contributes to the literature in two ways. First, the impact of MFG on adoption of agricultural technologies is evaluated through the time the farmers with MFG take to adopt a given technology compared to those without MFG. Two hypotheses are tested. i) MFD increases the speed of adoption. ii) The longer the farmer holds MFG the shorter the waiting time to switch from traditional to improved agricultural technologies. A flexible parametric proportional-hazards approach is used to test these hypotheses. Second, to resolve the mixed effects of MFG on farm performance (crop productivity), a non-monotonic inefficiency model of Wang (2002) is used. This model has the ability to determine, within the sample, whether MFG has a positive and negative impact on production efficiency. We demonstrate that long MFG significantly reduces the adoption lag and improves farm performance conditional on a sustainable extension service delivery system. We provide this evidence using farm household data collected by the Consortium for Improving Agriculture-based Livelihoods in Central Africa (CIALCA) in Rwanda, Burundi and the Democratic Republic of Congo (for details, see http://www.cialca.org).

The rest of the paper is organized as follows. Section two describes the analytical model. Section three describes the source of the data used. Section four reports and discusses the results. Section five concludes.

2. Analytical model

2.1. Duration analysis

The analytical strategy described here is based on Wooldridge (2010). Duration analysis examines the time elapsed until a certain event occurs. In this paper, duration analysis models the farmers' decision to adopt improved agricultural technologies at some point after household formation[2], where the waiting time to adoption (adoption lag) is defined as the number of years

[2] The MFG information was collected for the household head or spouse.

between the farmers' first exposure to the possibility ('risk') of adoption and the actual adoption. The year of household formation is chosen as the initial exposure to the risk of adoption because it is assumed that that is when an individual starts to make independent production decisions[3].

The empirical model to estimate the probability of discontinuing the waiting time to adoption after household formation follows the hazard rate function (Wooldridge, 2010), and is represented as:

$$\log(t) = \text{¢}_m MFG + \text{¢}\, w + \pm\text{¶} \tag{1}$$

where t is the adoption lag, δ_m and δ are parameters to be estimated, and δ_m is a parameter of interest which measures the effect of MFG on the probability of ending the adoption lag, w is the vector of household characteristics, ¶ is the error term scaled by the inverse of the shape parameter (°) capturing the monotonic time dependence (± = 1/°). The Weibull distributional functional form, transformed using an accelerated failure time model (Wooldridge, 2010), was used to estimate (1).

2.2. Stochastic production frontier

A stochastic production frontier model determines the relationship between a single output (y_i) produced by household i and a vector of productive inputs (x_i) used. This paper implements a model of Coelli *et al*. (1999) that has the ability to accommodate 'environmental factors' in both the production frontier and technical inefficiency functions. Environmental factors include physical, managerial and organizational characteristics of the farmer. The empirical stochastic production frontier model is given as:

$$\ln y_i = \sim_0 + \sum_{j=1}^{3} \sim_j \ln x_i + \frac{1}{2}\sum_{j=1}^{3}\sum_{k=1}^{3} \sim_{jk} \ln x_{ij} \ln x_{ik} + \sim_m MFG_i + \frac{1}{2}\sim_m MFG_i^2 + \sum_{j=1}^{3} \sim_{jm} \ln x_{ij} MFG_i + v_i - u_i \tag{2}$$

[3] As expected, however, there are some households which had not yet adopted at the time of data collection. In analysis, these households are right censored implying that the possibility of adoption continues beyond the survey time, and it is possible that they may choose to adopt at some unobservable time in future. Also, because of data limitations, any subsequent decision to disadopt, for adopters, is not modeled in this paper.

where $u_i = z_i \quad + £_i$,

ln is natural logarithm, MFG is included to test whether it has a direct effect on productivity, v_i is the symmetric sampling and measurement error with mean zero, u_i is the farmer's non-negative technical inefficiency[4], which can be explained by a vector of independent variables z_i (with MFG_i included), α_0, α_j, α_m, α_{jm}, β, $\alpha_{jk} = \alpha_{kj}$ are parameters to be estimated, and ε_i is the error term.

Equation (2) was estimated using the non-monotonic inefficiency model of Wang (2002). The model allows z_i to have, within the sample, both positive and negative effects on the technical inefficiency. For example, z_i can increase (or reduce) the efficiency level when the values of z_i are within a certain range, and can reduce (or increase) efficiency level for values outside the range. Equation (2) is also used to estimate the marginal effect of z_i on technical inefficiency. The marginal effects of z_i measure the change in output y_i for a unit change in z_i as follows:

$$\frac{\partial E(\ln y_i)}{\partial z_i} = -\frac{\partial E(u_i)}{\partial z_i}, \text{ specifically } \frac{\partial E(\ln y_i)}{\partial MFG_i} = -\frac{\partial E(u_i)}{\partial MFG_i} \tag{3}$$

The estimation challenge faced, however, is correct identification of both equations (1) and (2). The estimation of these equations is potentially contaminated by the selectivity bias due to both subjective sampling of households and participation in farmer groups for two reasons. First, farmer groups are often located in accessible locations such as near market areas and all weather roads (Abate *et al*., 2013). This leads to sample selection bias since those households in accessible location are, by study design, selected. Second, the wealth status influences the farmers' decision to participate in farmer groups. Evidence shows that wealthy individuals are less likely to participate in farmer groups (Bernard *et al*., 2008; Abate *et al*., 2013).

To overcome these challenges, the sampling design for the data used in this paper attempted to control for sample selection bias. The sampling procedure was clustered into two groups. First, the intervention sites in which CIALCA technologies were promoted and disseminated. Second, the control sites which were not exposed to CIALCA technologies. The

[4] A farmer is technically inefficient if he/she does not minimize inputs given the outputs, or alternatively, technical efficiency is measured as the ratio between the observed output and the maximum output conditional on fixed input assumption.

selection of both sites was based on similar agro-ecological conditions, population pressure and general location characteristics (for details, see Macharia *et al*., 2012).

To further reduce selectivity bias, the estimation strategy implemented in this paper utilizes the propensity score matching approach (PSM) (Dehejia and Wahba, 2002) to develop a subset of farmers without MFG which has similar characteristics to farmers with MFG (see Mayen *et al*., 2010 for detailed discussion). The selection of the subset of farmers without MFG follows three steps. First, we estimate a probability model of participation in farmer groups and then compute the propensity score of being a member for each observation. Second, each farmer with MFG is then matched to a non-member farmer with a similar propensity score using the single-nearest-neighbor matching method. Non-members not matched are not included in the analysis. Third, equations (1) and (2) are estimated on both original (unmatched) and matched samples to evaluate the degree of selection bias.

The major limitation of the PSM approach is that it does not control for unobservable heterogeneity that may influence the decision to participate in farmer groups. However, Imbens (2004) shows that unobservable heterogeneity that influences the decision to participate in farmer groups is independent of the outcomes of interest. The additional drawback of PSM approach is that it is designed for binary treatment effects. That is, the PSM approach enables us to measure the effects of being a member in famer groups on the speed of adoption, but not the heterogeneity of treatment effects arising from the duration of MFG. Having MFG can yield heterogeneous effects in terms of benefits and the duration of providing these benefits whose supply, which in turn is dependent on the duration of MFG. The benefits can include easy access to inputs, agricultural trainings, credit services and collective marketing and procurement of inputs at subsidized prices. To assess the heterogeneity of MFG, we utilize the dose-response function (Hirano and Imbens, 2004) in which the treatment variable takes on continuous values. The dose-response function (DRF) yields generalized propensity score (GPS), which has similar properties of the binary treatment propensity score. The DRF also allows us to relate each value of the dose (i.e., years of MFG) to the farmer's probability of switching from traditional technologies to adoption of improved ones. That is, the DRF is designed for analyzing the effect of treatment intensity implying that only farmers with MFG are included in estimation of this function. The details of implementation of the DRF are well documented in Bia and Mattei (2008) and are not repeated here to save space.

3.0 Data sources

The paper uses data collected by CIALCA in Rwanda, Burundi and Democratic Republic of Congo (DRC). Data collection followed a multi-stage sampling procedure to randomly select a total of 913 farm households from both intervention and control villages (see Macharia *et al*., 2012 for details)[5]. Table 1 reports descriptive results for both unmatched and matched samples following the procedure described in section 2. The PSM subsample was selected based on the procedure described in section 2.2. A probit model was used to generate the propensity scores of participation in farmer groups. The estimates from probit model are reported in Appendix Table A1.

The crop production data were collected for one crop season of 2010. The value of crop production per hectare was computed as the sum of all crop harvests by each household multiplied by the respective farm gate prices, and then divided by the total operated crop area. Where farm gate price for a given crop was missing, a median price generated at the level of district (Rwanda), territoire (DRC) or commune (Burundi) was used. The local currencies in the three countries were converted to United States dollars (US$) using the following average exchange rates for 1 US$ for 2011: Burundi (1300), DRC (900), and Rwanda (600).

Table 1 here

3.1 Farmers membership to groups and sources of technologies

CIALCA targeted farmers organized in groups or associations whose main objective promoted improvement of agricultural productivity or collective marketing. With the aim of reducing on technology dissemination and transaction costs, CIALCA identified these groups with the help of local partner organizations. The sample data used in the analysis involved 46% of surveyed farmers who had membership in farming oriented groups (Figure 1). Some farmers also had

[5] It is important to note that the number of observations used in the analysis varies depending on the technology being considered, the PSM procedure, and missing data information.

membership in other groups not targeted by CIALCA. Table 1 also reports that some farmers or members of their households had multiple memberships in different groups.

Figure 1 here

In some areas, CIALCA provided the technologies and trainings directly to farmers and in other areas, these services were provided indirectly through local partners. The technologies promoted and disseminated included: improved germplasm (soybeans, bananas, maize, cassava, climbing beans, pigeon peas, and bush beans), improved crop management systems (intercropping with recommended plant spacing, organic and inorganic fertilizer application, crop rotation, improved fallow), integrated pest management practices (use of clean banana planting materials, de-budding and removal of sick banana plants), and post harvest technologies (business plans, marketing and soybean transformation into milk, cake, and *tofu*). It is important to note that some farmers were already using some of these technologies or some components of the technology package, but with limited training on their application. Figure 2 reports different sources of technologies among farmers who were engaged in production of CIALCA mandate crops. The figure reports information of on key providers of new technologies which included government extension agents (GV'T), CIALCA and extension agents from non-governmental organizations (NGO). For farmers who have ever used or were using improved technologies, Figure 2 reports that a fairly a good number of them sourced technologies from CIALCA and government extension agents and a small number did so from NGOs.

Interestingly, the mode of dissemination of technologies by government extension systems and NGOs across CIALCA countries was largely through direct contacts with farmers not farmer groups. Our sample data shows that only one farmer received improved cassava technologies from both government extension agent and farmer groups and another one from NGO extension agent and farmer groups. No other farmers were able to receive technologies through farmer groups except if associated with CIALCA. Thus, CIALCA provides a suitable case scenario to determine the role of farmer groups play in improving adoption of agricultural technologies.

Figure 2 here

4. Estimation of main results

4.1. Determinants of adoption lag of agricultural technologies

Table 2 reports two sets of results from the duration analysis using equation (1). The upper panel reports results from the subsample obtained through PSM. The bottom panel reports results from the DRF, which involves a subsample of farmers with MFG only. To save space, only results obtained for matched subsamples from PSM and DRF approaches and variables of interest are reported. Full results are available from the authors on request. Household characteristics included in the estimations but excluded from the table are: education of the household head (dummy), household size, logarithm of off-farm income, number of months of food insecurity in a year, distance to the nearest market and country dummies. The tests for common support assumption (Dehejia and Wahba, 2002; Hirano and Imbens, 2004) for PSM and DRF are reported in Appendix Figures B1 and B2. The figures show that the common support assumption holds.

In interpreting the estimates, we multiply the coefficient by 100 to obtain semielasticity of covariates. A negative coefficient means a shorter length of time to (or a higher probability of), and a positive coefficient indicates a longer length of time to (or a lower probability of) adoption of agricultural technologies.

The results indicate that being a member of farmer group reduced the time lag to adopt improved legumes and use of manure by about 14% and 23%, respectively. That is, having MFG increases the chances of discontinuing the waiting time to adopt some agricultural technologies. Compared to other providers of extension services, the results show that CIALCA played a key role by disseminating technologies through farmer groups. Farmers who received extension services from CIALCA had significantly higher probability of adopting technologies than those who received similar services from NGOs. In particular, CIALCA training raised the probability of adopting improved technologies by about 26% for legume and maize varieties, 20% for post-harvest practices and cassava varieties, and 12% for banana varieties.

Interestingly, we obtain similar results when we limit the analysis to a subsample of farmers with MFG. Most importantly, there is evidence to suggest that there exists heterogeneous effects of duration in farmer groups on the farmers' decision to discontinue adoption lag of agricultural technologies. The results in the bottom panel of Table 2 indicate that an increase of MFG by one year reduced the time lag to adopt improved legumes, banana, maize and cassava varieties, use of manure and improved post-harvest technologies by 3 – 7%. That is, the results are consistent with the stated hypothesis that MFG reduces the adoption lag.

The farmers receiving extension services from CIALCA and NGOs had a high likelihood of adopting technologies earlier than those receiving the same services from government programs. Farmers receiving extension services from government agents were more likely to prolong the pre-adoption period of improved legume and maize varieties, but this effect was insignificant for other considered technologies. These results are not surprising and are supported by earlier work which indicates that NGO extension service delivery is more important than that of governmental extension systems in closing agricultural technology gap (Dinar *et al.*, 2007). This is because the former emphasizes practical application of disseminated technologies, while the latter addresses a wide range of agricultural constraints (Hanson and Just, 2001).

Table 2 here

4.2. Interaction effects between MFG and providers of extension services

The negative and significant estimates of MFG, number of visits by NGO extension agents and CIALCA suggest that these non-state means of technology dissemination play a key role in promoting adoption of technologies. However, these findings raise further research questions. If early and high adoption of agricultural technologies is achieved through farmer groups, the formation of which is sometimes influenced by NGOs, does the effect of MFG on the adoption lag depend on the source of extension services? Answering this question involves testing whether there is a significant interaction effect between MFG and different providers of extension services. Table 3 reports results for both PSM and DRF subsamples.

It is important to note that adding interaction terms changes the interpretation of all the coefficients of variables of interest. Since the interaction term shows that the effect of MFG on the adoption lag depends on access to extension services, the effect of MFG on the adoption lag depends on the magnitudes of the coefficients on the interaction term and the source of extension services. For example, for farmers who did and did not receive the CIALCA training, implying that they are assigned the values of 1 and 0, respectively, the effect of MFG on the delay to adopt improved legume varieties, correspondingly, reduces by 24.9% (–0.065*1 – 0.184*1) and 0% (–0.020*0 – 0.184*0). The presence of a significant interaction term indicates that the effect of MFG on the adoption lag is different at different values of the different sources of extension services. The non-significant interaction term means that the effect of MFG on the adoption lag does not depend on access to extension services.

In general, the results show that an interactive relationship between MFG and access to CIALCA extension services strengthened the effect of MFG on the adoption lag. That is, coefficients on the interaction term, MFG x CIALCA, are all significant and negative except for banana and maize technologies. This implies that early adoption of considered technologies occurred among farmers with MFG who received CIALCA extension services. On the other hand, the coefficients on the interaction terms, MFG x GEA and MFG x NEA had both negative and positive effects on the adoption lag. Specifically, early adoption of improved legumes, use of manure and post-harvest technologies, and late adoption of improved banana, maize and cassava varieties, occurred among farmers with MFG who received government extension services. For farmers who received extension services from NGO and had MFG, adopted use of manure and post-harvest technologies but delayed adoption of improved banana and cassava varieties.

Table 3 here

For the subsample of farmers with MFG, the interaction effects with providers of extension services do not, generally, matter much. This is possibly because farmers with MFG had an advantage of receiving of technologies, especially from CIALCA, regardless of whether they received extension services or not. However, given the existence of heterogeneity in terms of duration of MFG, it is instructive to examine how the interaction effects vary with the years of MFG. That is, we further examine whether access to CIALCA extension services reduces the adoption lag faster than access to government and NGO extension services or vice versa for farmers at different levels of MFG. The results in Table 3 do not provide sufficient explanation, since the size and precise relationship of interaction effects is not easy to examine from the coefficients alone. The interpretation becomes more complicated when one or more of the coefficients of the main variables has an opposite sign. To overcome this, we plotted the predicted adoption lag against MFG to interpret them visually. This was done by generating predicted values of adoption lag using the mean values of number of extension visits by both government and NGO extension agents for only farmers who received these visits. Similarly, farmers who only received CIALCA training were considered. Then the predicted values of adoption lag were plotted against different levels of MFG (Figure 3).

Figure 3 here

The solid curve (Figure 3) was predicted assuming that all variables were fixed except MFG to provide a baseline reference. With the exception of improved cassava varieties and post-harvest technologies, the solid curve indicates that MFG alone considerably delays adoption of other technologies considered. The figure shows interesting patterns of how different sources of extension services moderate the effect of MFG on adoption lag. Two key findings are noteworthy.

First, compared to farmers with MFG and benefiting from NGO extension programs, there are strong opportunities for those farmers receiving extension services from government programs to make early decisions to adopt improved banana and cassava varieties, and post-harvest technologies. This is because, in the study areas, banana are a major food and source of income and hence ensure food and cash income; cassava withstands variability in weather patterns better than other crops which makes it a food security crop, and post-harvest technologies guarantee both food security and value addition (Macharia *et al*., 2012). It is not surprising, therefore, that farmers would prefer adopting technologies that ensure food security and cash income first to other technologies. This preferential adoption may be partly influenced by reduced uncertainty about these technologies, because government programs have the ability to sustain extension information delivery which reduces uncertainty surrounding agricultural technologies (Rivera and Alex, 2004). More precisely, government extension systems often guarantee sustainability and scaling up of agricultural technologies introduced by NGO extension programs which are often time bound (Rivera and Qamar, 2003), and government extension services delivered through farmer groups have been found to improve both food security (Wendland and Sills, 2008; Fisher and Lewin, 2013).

Second, unlike the effect of government extension delivery, CIALCA moderated the effects of MFG on reducing the delay to adopt all technologies of focus. Although one may argue that CIALCA falls under the NGO agricultural extension system, CIALCA used a three-pronged approach, which is, in some cases, ignored by other NGOs (Macharia *et al*., 2012). First, CIALCA developed an active working collaboration with national research systems and local development agencies which have a more or less permanent presence in the study areas. Some of these agencies have developed approaches that ensure sustainability of disseminated knowledge and skills by recruiting local farmers to become trainers of trainees in their communities. Second, CIALCA used a farmer-participatory approach to disseminate technologies. This approach allowed farmers to evaluate and select appropriate technologies suitable for their resources. Third, CIALCA disseminated technologies through farmer groups. Farmer groups play an important role in knowledge and information management and sharing through regular meetings. The combination of these effects may explain why CIALCA has a slightly stronger effect than government extension systems, and a much stronger effect than other NGO extension programs on reducing the adoption lag.

4.3 Adoption lag and source of technologies

The preceding discussion has focused on the effect of different sources of extension training conditional on MFG, but not on the effects of different sources of technologies. It is important to distinguish these effects since they might have different policy implications. Results in Table 4 show that different sources of technologies do not matter as much as the different sources of extension services in influencing the farmer’s decision to end adoption lag. The results show that all sources of technologies (CIALCA, government and NGO extension systems) significantly reduce the waiting time to adopt technologies. Similarly, the interaction effects between different sources and MFG do not play a significant role in reducing the adoption lag with an exception of improved legumes (GEA x MFG), post-harvest technologies (NEA x MFG) and improved banana varieties (CIALCA x MFG). These findings suggest that the provision of extension services through farmer groups can be an effective approach for successful adoption of technologies, while dissemination through farmer groups without simultaneous provision of extension services does not necessarily lead to successful adoption of technologies.

Table 4 here

4.4. Farm performance and membership in farmer groups

This section shows how MFG affects farm performance in terms of technical efficiency and its marginal effect on farm productivity. Table 5 reports the summary statistics of technical efficiency levels and marginal effects estimated from equations (2) and (3), respectively. Full results of the stochastic production frontier model, technical inefficiency shifters and their respective marginal effects are not reported to save space, but they are available from the authors on request.

The overall results of farm performance rather than individual crop performance are reported. Estimation of stochastic production frontier models for individual crops failed to achieve convergence for some crops due to small sample size and limited variation among some covariates. For those crops where convergence was achieved, results do not differ appreciably from the ones reported. To test the null hypothesis that MFG has no direct effect on farm productivity, a joint test of coefficients on MFG, its squared term, and respective interaction terms was done. The chi square value (p-value) was 5.09 (0.532), which reflects failure to reject the null hypothesis. That is, MFG does not have direct effect on farm productivity in our sample of farm households.

The estimates in Table 5 show that the average technical efficiency is as low as 46% of the potential farm productivity, implying that a 54% increase in farm productivity is still achievable with the current use of technologies and same level of input use. This technical efficiency level corresponds to one achieved by smallholder farmers in Côte d'Ivoire, which was as low as 36% without controlling for environmental factors such as soil erosivity, pests, diseases, and rainfall (Sherlund *et al*., 2002). Table 5 also compares technical efficiency of different farmer categories using a t-test. Farmers with MFG are about 7% more efficient than those without. Similarly farmers who received extension services from CIALCA and NGOs were 11% and 8% more efficient in improving their productivity than those who did not receive these services.

Table 5 here

To further understand the relationship between farm performance and MFG, we plotted technical efficiency levels against MFG (Figure 4, left panel). The plot shows an inverted-J shaped relationship between technical efficiency and MFG. However, care should be taken in interpreting this relationship; only about 3% of the sample had MFG spanning more than 10 years. Despite this caution, there is evidence to show that information and knowledge sharing in early years after entry in farmer groups improves farm productivity through increased technical efficiency of both technology and input use. This is possibly because the new adopters are still learning by doing and enthusiastic to use new technologies to produce toward the frontier output level. As time passes, however, the technical efficiency improves at a decreasing rate up to about 4.2 years of MFG, beyond which technical efficiency declines gradually with more time of MFG possibly due to diminishing returns associated with lengthy MFG.

Figure 4 here

The lower panel of Table 5 further highlights the importance of MFG and extension services on technical inefficiency. The overall average marginal effect of MFG on technical inefficiency is -0.075, suggesting an increase in farm level output by 7.5% for every additional year of membership. The average marginal effects of extension delivery from government and NGOs are -0.043 and -0.126, respectively, which translate into corresponding increases in farm level output by 4.3% and 12.6%. However, the marginal effects of these variables, as shown in Table 5, range from negative to positive values suggesting that these variables have non-monotonic effects on technical inefficiency within the sample and so is on the farm output level. To visually demonstrate this and relate it to MFG, the right panel of Figure 4 plots the marginal effects of MFG and extension visits on the length of MFG for the matched sample. For all the three curves, the marginal effects tend to be negative in the early years of MFG, indicating an improvement in technical efficiency. However, this improvement diminishes gradually over time as indicated by the zero-crossing curves.

5. Discussions, conclusions and policy implications

The study analyses the effect of membership in farmer groups (MFG) on the farmers' time lag to adopt agricultural technologies, using duration analysis, and farm performance, using a non-monotonic inefficiency effects model. The findings indicate that member farmers are more likely to be early adopters of agricultural technologies than non-members. However, this early adoption depends on the length of membership, the type of technology being disseminated, and the type of extension provider (government or NGOs).

Membership alone is more effective in reducing the time lag to adopt improved crop varieties and application of soil fertility inputs (chemical and organic fertilizers) among farmers with a short period of membership than those with a long period. A similar trend of adoption was observed among member farmers who received extension services from NGOs, but not from government extension system and CIALCA. However, the findings show that the combination of long duration in farmer groups and extension service delivery from government or CIALCA accelerated early adoption of agricultural technologies much faster than MFG, or NGO extension service delivery, alone. This is because extension service delivery from government programs is to some extent sustainable compared to that from NGOs, whose service delivery often ends with the project life span, which is commonly short. However, this does not mean hopelessness for NGOs in achieving successful early adoption of technologies. Like other NGOs, CIALCA had active dissemination of technologies in the Great Lakes region of Africa for a short period of about four years, and yet had effects on adoption lag similar to those of the government extension service, largely because, in addition to developing a strong collaboration with local partners and farmer groups, CIALCA used a farmer participatory approach in disseminating technologies, wherein farmers evaluated and selected technologies appropriate to them. Strengthening the functioning of farmer groups to attract non-members to join or to retain membership in farmer groups, combined with incentives to improve non-governmental extension systems involving participatory approaches come out as the key policy implications drawn from the study findings.

Despite NGOs having weak effects on influencing smallholder farmers to make early decisions to adopt technologies through farmer groups, they play a key role in improving farm level productivity compared to government extension systems. The findings show that farmers who received extension services from NGOs were more technically efficient than those who received similar services from a government extension system by 8% and as much as 11% if the farmer received CIALCA training. This is possibly due to differences in resources between public (government) and private extension services (NGOs and CIALCA): the government extension services have less operational budget and less trained extension agents, which makes its staff ill motivated compared to NGO staff. Thus, the impact of government extension services on efficiency can be only lower.

An important finding in the case of Great Lakes region of Africa is that MFG has non-monotonic effects on technical inefficiency, that is, during the initial years of MFG, the marginal impact of membership on technical efficiency is positive, whereas it is negative for long duration of membership. These findings point toward further research to investigate how and why farmers with long periods of membership have lower farm productivity than those with short periods in farmer groups.

Overall the findings demonstrate that farmer groups can be, and are, an appropriate channel to enhance early adoption of agricultural technologies and improve farm level productivity. However, development agencies and researchers can strengthen this channel to achieve successful early adoption through: firstly, a 'synergistic' intervention, in the sense that the effect of simultaneous increases in both MFG and extension service delivery is more than the combined effects of the same increases made individually for each factor; secondly, promotion of farmer-participatory approaches in technology evaluation and selection to enable farmers to choose technologies suitable to their socio-economic and physical conditions; and thirdly, development of a dissemination and extension strategy which ensures sustainable service delivery to enhance adoption of technologies.

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Tables

Table 1. Description of variables included in the study for matched and unmatched samples

	Members of farmer groups (N=420)		Unmatched non-members of farmer groups (N=493)		Matched non-members of farmer groups (N=347)	
Variable	mean	Standard error	mean	Standard error	mean	Standard error
Male headed households (0/1)	0.823 [418]	0.019	0.801	0.018	0.822	0.019
Head with formal education (0/1)	0.750	0.021	0.688	0.021**	0.738	0.024
Household size (persons)	6.09	0.12	5.63	0.11***	6.02	0.13
Head's main occupation is farming (0/1)	0.893	0.015	0.886	0.014	0.896	0.016
Number of food insecure months in a year	3.05	0.08	3.08	0.08	3.02	0.09
Distance from home to nearest market (km)	4.08	0.33	4.14	0.32	4.11	0.37
Annual # of visits by government extension agent	2.50	0.24	2.35	0.25	2.40	0.27
Annual # of visits by NGO extension agent	3.08	0.22	1.06	0.11***	2.66	0.23***
Household received CIALCA training (0/1)	0.39	0.02	0.01	0.01***	0.39	0.03***
Total land operated (ha)	1.68	0.30	1.90	0.27	1.79	0.36
Labor used in crop production (person days)	86.80	4.24	63.06	2.93***	78.03	3.97
Amount of fertilizers applied (kg)	362.80	40.93	286.77	48.53	359.36	46.89
Value of farm assets (US$)	2559.9	149.2	1921.8	241.1**	2428.2	247.6
Off-farm income per adult equivalent (US$)	29.93	8.42	269.0	225.3	32.79	10.15
Farm income per adult equivalent (US$)	76.30	9.15	81.74	16.51	75.36	9.82
Amount of credit received (US$)	17.08	3.57	13.32	3.89	17.33	4.04
Value of crop production per ha (US$)	535.1 [364]	63.8	599.3 [420]	68.9	471 [297]	55.4
Other household member(s) with MFG apart from household head (0/1)	0.345	0.023	0.004	0.003***	0.213	0.022***
Other household member(s) with membership in other groups apart from farmer groups (0/1)	0.295	0.022	0.263	0.019	0.277	0.024
Head's membership in other groups apart from farmer groups	0.645	0.024	0.509	0.023***	0.631	0.026

Figures in square brackets are numbers of observations which differ from the overall sample size. ***, **, * are significance levels at 1%, 5% and 10%, respectively

Table 2: Determinants of adoption lag of agricultural technologies

PSM subsample	Improved legumes	Improved banana	Improved maize	Improved cassava	Use of manure	Post-harvest
MFG (0/1)	-0.143*** (0.026)	-0.017 (0.017)	0.030 (0.036)	0.005 (0.034)	-0.229*** (0.065)	0.006 (0.007)
Number of visits by GEA[a]	0.009** (0.003)	0.006 (0.007)	0.030*** (0.009)	0.006 (0.008)	0.006 (0.006)	0.004 (0.006)
Number of visits by NEA[a]	-0.035*** (0.010)	-0.036*** (0.004)	-0.042*** (0.001)	-0.034*** (0.005)	-0.036** (0.012)	-0.031** (0.014)
Received CIALCA training (0/1)	-0.260** (0.109)	-0.124*** (0.027)	-0.263*** (0.044)	-0.198* (0.121)	-0.017 (0.251)	-0.202* (0.105)
Other household characteristics	yes	yes	yes	yes	yes	yes
Constant	-6.570*** (0.369)	-6.778*** (0.272)	-7.166*** (0.958)	-7.255*** (0.637)	-6.714*** (0.645)	-6.346*** (0.154)
Log likelihood	-465.226	-449.308	-338.468	-403.655	-418.067	-492.848
Number of observations	565	499	412	480	516	523
DRF subsample						
MFG (years)	-0.045* (0.026)	-0.033** (0.015)	-0.033* (0.020)	-0.066** (0.026)	-0.047** (0.023)	-0.066*** (0.017)
Number of visits by GEA[a]	0.009 (0.027)	-0.021 (0.025)	0.040** (0.017)	-0.013 (0.021)	0.006 (0.017)	-0.006 (0.017)
Number of visits by NEA[a]	-0.044** (0.020)	-0.033** (0.017)	-0.047** (0.020)	-0.030* (0.017)	-0.008 (0.015)	-0.019 (0.013)
Received CIALCA training (0/1)	-0.414** (0.174)	-0.077 (0.130)	-0.321* (0.176)	-0.269* (0.151)	-0.338** (0.171)	-0.223* (0.129)
Other household characteristics	yes	yes	yes	yes	yes	yes
Constant	-5.974*** (0.710)	-7.089*** (0.602)	-6.351*** (0.758)	-6.041*** (0.701)	-5.363*** (0.709)	-5.793*** (0.566)
Log likelihood	-244.37**	-237.40***	-201.27***	-233.62*	-235.25	-263.81***
Number of observations	332	288	245	279	300	296

Figures in parentheses are standard errors. ***, **, * are significance levels at 1%, 5% and 10%, respectively.
Constants in the upper middle panels are not reported to save space.
[a]GEA - government extension agents, [b]NEA - non-government extension agents.

Table 3. Adoption lag and the interaction between MFG and providers of extension services

PSM subsample with interactions	Improved legumes	Improved banana	Improved maize	Improved cassava	Use of manure	Post-harvest
MFG (0/1)	-0.065*** (0.018)	0.026* (0.015)	0.017 (0.018)	0.083*** (0.003)	-0.194*** (0.014)	-0.077*** (0.020)
Number of visits by GEA[a]	0.011*** (0.001)	0.013*** (0.003)	0.026*** (0.004)	0.015** (0.005)	0.009 (0.009)	0.013*** (0.004)
Number of visits by NEA[b]	-0.024** (0.010)	-0.027*** (0.002)	-0.042*** (0.003)	-0.041*** (0.002)	-0.062*** (0.009)	-0.058*** (0.007)
Received CIALCA training (0/1)	-0.136*** (0.014)	-0.172*** (0.028)	-0.190*** (0.054)	-0.043 (0.060)	0.179* (0.107)	-0.446*** (0.051)
Interaction between MFG and number of visits by GEA	-0.009*** (0.002)	-0.018** (0.006)	0.010*** (0.002)	-0.026*** (0.000)	-0.006*** (0.001)	-0.023*** (0.000)
Interaction between MFG and number of visits by NEA	-0.015 (0.010)	-0.012** (0.006)	-0.001 (0.007)	0.014*** (0.000)	0.040*** (0.007)	0.041*** (0.007)
Interaction between MFG and CIALCA training	-0.184*** (0.025)	0.073** (0.030)	-0.099 (0.066)	-0.229*** (0.056)	-0.339*** (0.025)	0.326*** (0.036)
Other household characteristics	yes	yes	yes	yes	yes	yes
Constant	-6.592*** (0.349)	-6.811*** (0.305)	-7.147*** (0.980)	-7.314*** (0.603)	-6.743*** (0.654)	-6.322*** (0.186)
Log likelihood	-464.846	-448.881	-338.350	-402.941	-417.073	-490.406
Number of observations	565	499	412	480	516	523
DRF subsample with interactions						
MFG (years)	-0.008 (0.030)	-0.022 (0.027)	-0.009 (0.032)	-0.063* (0.037)	-0.007 (0.035)	-0.059** (0.030)
Number of visits by GEA[a]	0.009 (0.028)	-0.018 (0.024)	0.038 (0.024)	-0.036 (0.025)	0.017 (0.024)	-0.004 (0.018)
Number of visits by NEA[b]	-0.039* (0.020)	-0.038** (0.016)	-0.044** (0.022)	-0.028 (0.017)	-0.010 (0.017)	-0.018 (0.013)
Received CIALCA training (0/1)	-0.209 (0.217)	0.001 (0.167)	-0.199 (0.221)	-0.122 (0.183)	-0.116 (0.221)	-0.184 (0.169)
Interaction between MFG and number of visits by GEA	-0.002 (0.009)	-0.009 (0.007)	0.001 (0.007)	-0.025** (0.011)	-0.008 (0.006)	-0.005 (0.006)
Interaction between MFG and number of visits by NEA	0.009 (0.008)	0.008 (0.006)	-0.000 (0.007)	0.001 (0.007)	0.009 (0.007)	0.005 (0.005)
Interaction between MFG and CIALCA training	-0.110* (0.065)	-0.040 (0.039)	-0.050 (0.049)	-0.073 (0.053)	-0.111** (0.056)	-0.027 (0.040)
Other household characteristics	yes	yes	yes	yes	yes	yes
Constant	-6.341*** (0.697)	-7.410*** (0.605)	-6.598*** (0.753)	-6.642*** (0.706)	-5.658*** (0.701)	-6.178*** (0.553)
Log likelihood	-242.93**	-235.97**	-200.79**	-230.74*	-233.18*	-263.11**
Number of observations	332	288	245	279	300	296

Figures in parentheses are standard errors. ***, **, * are significance levels at 1%, 5% and 10%, respectively. Constants in the upper middle panels are not reported to save space.

[a]GEA - government extension agents, [b]NEA - non-government extension agents.

Table 4. Effects of source of technology and adoption lag

	Improved legumes	Improved banana	Improved maize	Improved cassava	Use of manure	Post-harvest
MFG (0/1)	-0.006***	-0.041	0.051	0.024	-0.015	-0.006
	(0.001)	(0.029)	(0.037)	(0.029)	(0.024)	(0.036)
GEA as source of technology	-1.475***	-14.738***	-17.135***	-16.695***	-1.523***	-16.749***
	(0.031)	(1.410)	(1.375)	(1.460)	(0.066)	(1.264)
NGO as source of technology	-14.936***	§	-17.048***	-15.987***	-8.926***	-0.068
	(1.356)		(1.302)	(1.371)	(1.483)	(0.094)
CIALCA as source of technology	-15.719***	-2.244***	-16.902***	-16.508***	-12.746***	-16.619***
	(1.409)	(0.005)	(1.436)	(1.317)	(1.366)	(1.340)
Interaction between GEA and MFG	-14.194***	12.806***	-0.019	0.215	0.210***	0.100
	(1.438)	(1.426)	(2.061)	(2.116)	(0.039)	(1.883)
Interaction between NEA and MFG	-0.796	§	0.287	-0.582	§	-16.583***
	(1.906)		(1.956)	(1.960)		(1.477)
Interaction between CIALCA and MFG	12.568***	-0.290***	13.766***	0.166	9.184***	0.022
	(1.411)	(0.006)	(1.448)	(1.903)	(1.400)	(1.905)
Other household characteristics	yes	yes	yes	yes	yes	yes
Constant	-6.728***	-6.877***	-7.295***	-7.444***	-6.989***	-6.423***
	(0.211)	(0.231)	(0.955)	(0.504)	(0.212)	(0.204)
Log likelihood	-413.822	-431.447	-300.648	-366.448	-383.853	-472.983
Number of observations	565	499	412	480	516	523

Figures in parentheses are standard errors. ***, **, * are significance levels at 1%, 5% and 10%, respectively.
Constants in the upper middle panels are not reported to save space.
§ dropped because to collinearity

Table 5. Means of technical efficiency and marginal effects for PSM matched sample

Technical efficiency	Household did not have …	Household had …	Difference in means
All households	0.459 (0.227) [710]	-	-
Membership in farmer groups (MFG)	0.426 (0.237) [357]	0.492 (0.212) [353]	-0.067***
CIALCA training	0.431 (0.227) [526]	0.538 (0.209) [184]	-0.107 ***
MFG and CIALCA training	0.470 (0.214) [208]	0.525 (0.206) [145]	-0.056**
Government extension services (GES)	0.449 (0.237) [362]	0.469 (0.216) [348]	-0.020
MFG and GES	0.499 (0.203) [167]	0.487 (0.220) [186]	0.013
Non-governmental extension services (NES)	0.419 (0.224) [356]	0.424 (0.222) [354]	-0.080***
MFG and NES	0.483 (0.200) [128]	0.498 (0.219) [225]	-0.015
Marginal effects		*Average*	
Average length of membership in farmer groups (years)		-0.075*** (0.007) [-0.841 : 0.537]	
Average number of visits by government extension agents		-0.043*** (0.004) [-0.447 : 0.257]	
Average number of visits by NGO extension agents		-0.126*** (0.008) [-1.069 : 0.444]	

***, **, * are significance levels at 1%, 5% and 10%, respectively. In the upper panel, figures in parentheses are standard deviations and those in square brackets are numbers of observations. In the lower panel, figures in parentheses are standard errors and those in square brackets show minimum and maximum values of marginal effects. The significance tests for marginal effects are bias-corrected and bootstrapped with 1,000 replications.

Figures

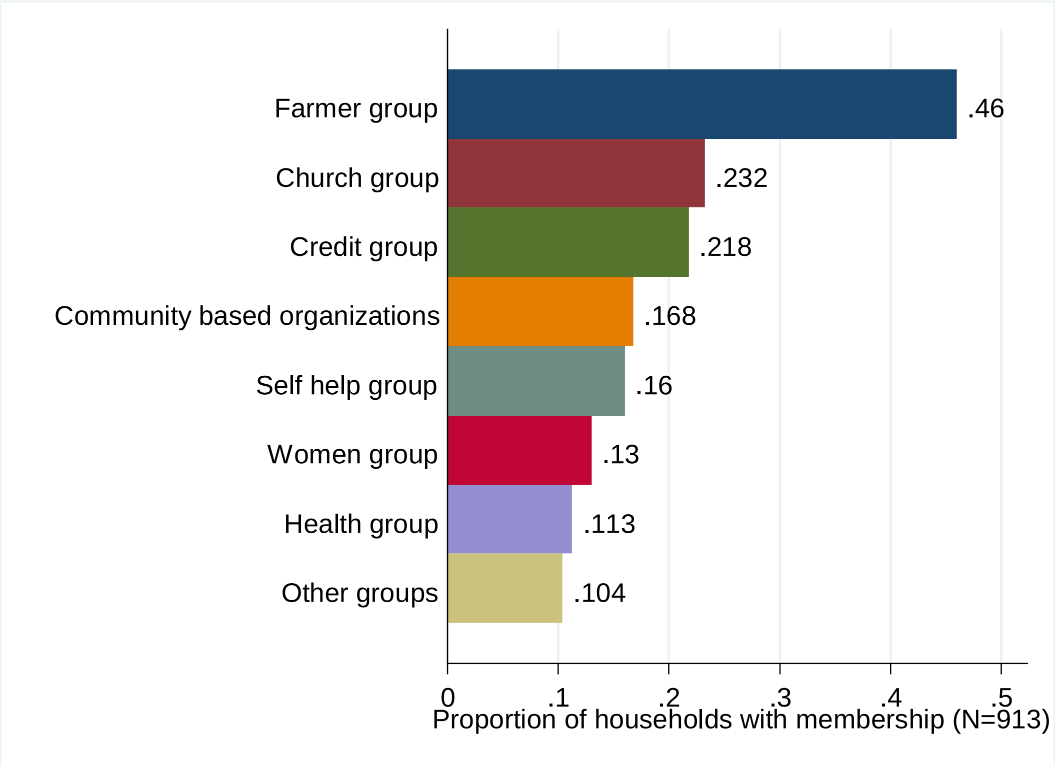

Figure 1. Farmers' membership in groups

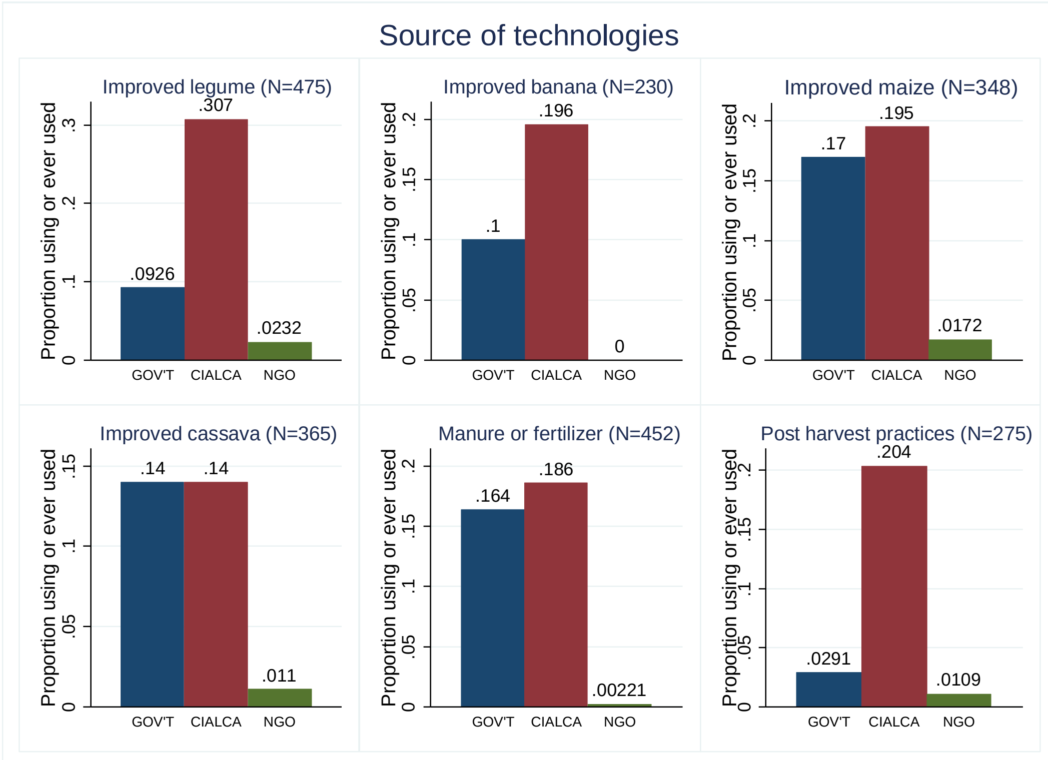

Figure 2. Source of technologies for farmers involved in the activity

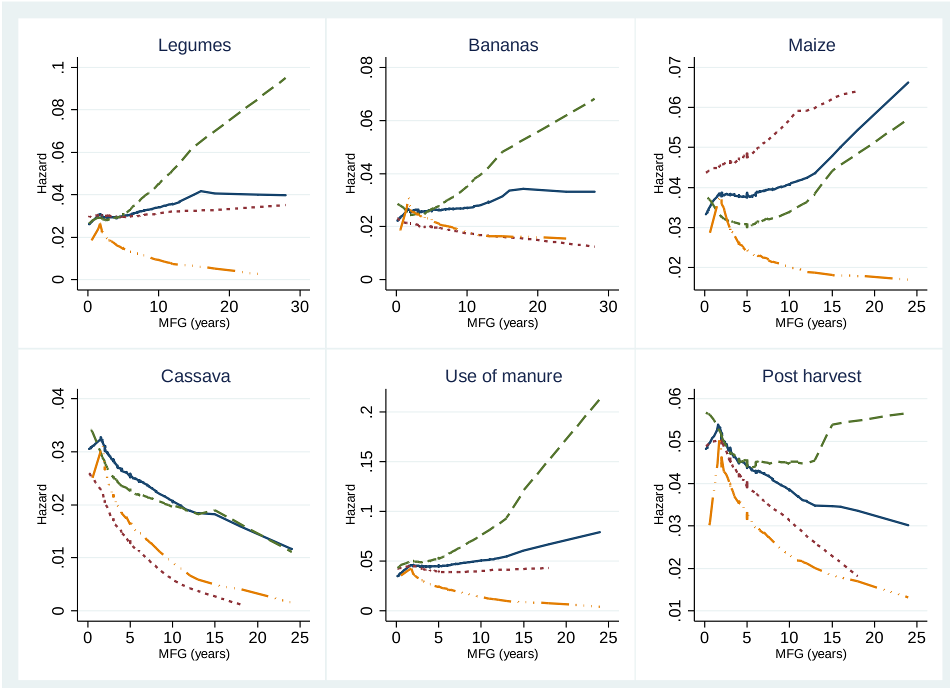

Figure 3. The probability of discontinuing the waiting time to adopt technologies plotted against the length of MFG. The solid line plots the effects of MFG alone, the dashed line plots interaction effects between MFG and NGO extension services, the dotted line plots the interaction effects between MFG and government extension services, the long dashed line with three dots plots the interaction effects between MFG and CIALCA training services.

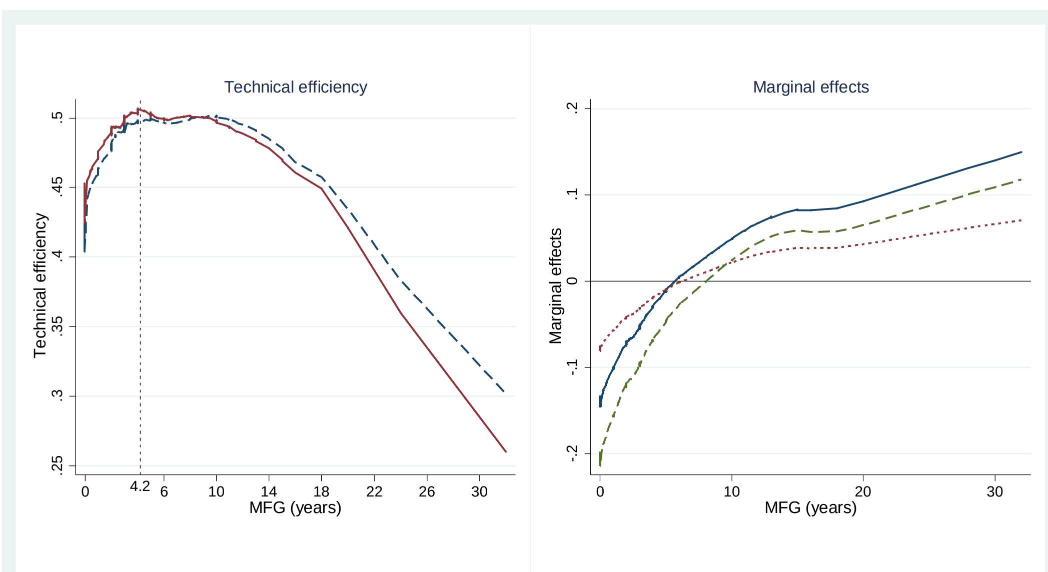

Figure 4. The left panel shows nonparametric prediction of technical efficiency on the length of MFG. The dashed line represents unmatched sample curve, and the solid represents PSM matched sample. The right panel plots PSM matched sample marginal effects of MFG (solid line), government extension delivery (dotted line) and NGO extension delivery (dashed line) on the length of MFG

Appendix A

Table A1. Determinants of membership in farmer groups

Dependent = Membership in farmer groups (0/1)	Probit estimates
Male headed household (0/1)	-0.173 (0.126)
Age of household head (years)	0.067** (0.024)
Age of household head (years) squared	-0.001** (0.000)
Household head attained education (0/1)	0.101 (0.113)
Household size	0.009 (0.023)
Log of farm income per adult equivalent (US $)	0.155** (0.075)
Log of farm income per adult equivalent (US $) squared	-0.026** (0.012)
Log of off-farm income per adult equivalent (US $)	-0.059** (0.028)
Log of amount of credit received (US$)	0.071* (0.037)
Log of value of farm related assets (US$)	0.055 (0.034)
Log of operated area (ha)	-0.148* (0.083)
Log of distance from home to nearest market (km)	0.042 (0.060)
Number of contacts with government extension agent in year previous to survey	0.022 (0.020)
Number of contacts with government extension agent in year previous to survey squared	-0.001 (0.001)
Number of contacts with NGO agent in year previous to survey	0.178*** (0.032)
Number of contacts with NGO agent in year previous to survey squared	-0.006*** (0.002)
Other household member(s) with MFG apart from household head (0/1)	2.619*** (0.321)
Other household member(s) with membership in other groups apart from farmer groups (0/1)	-0.431** (0.136)
Head's membership in other groups apart from farmer groups	0.332** (0.122)
Total labor used crop production (person days)	0.002** (0.001)
Country effects (Burundi compared to DRC)	-0.585*** (0.142)
Country effects (Rwanda compared to DRC)	-0.425** (0.139)
Constant	-2.459*** (0.592)
Log likelihood	-432.743***
Pseudo R2	0.3059
Number of observations	903

***, **, * are significance levels at 1%, 5% and 10%, respectively. Figures in parentheses are robust standard errors

Appendix A

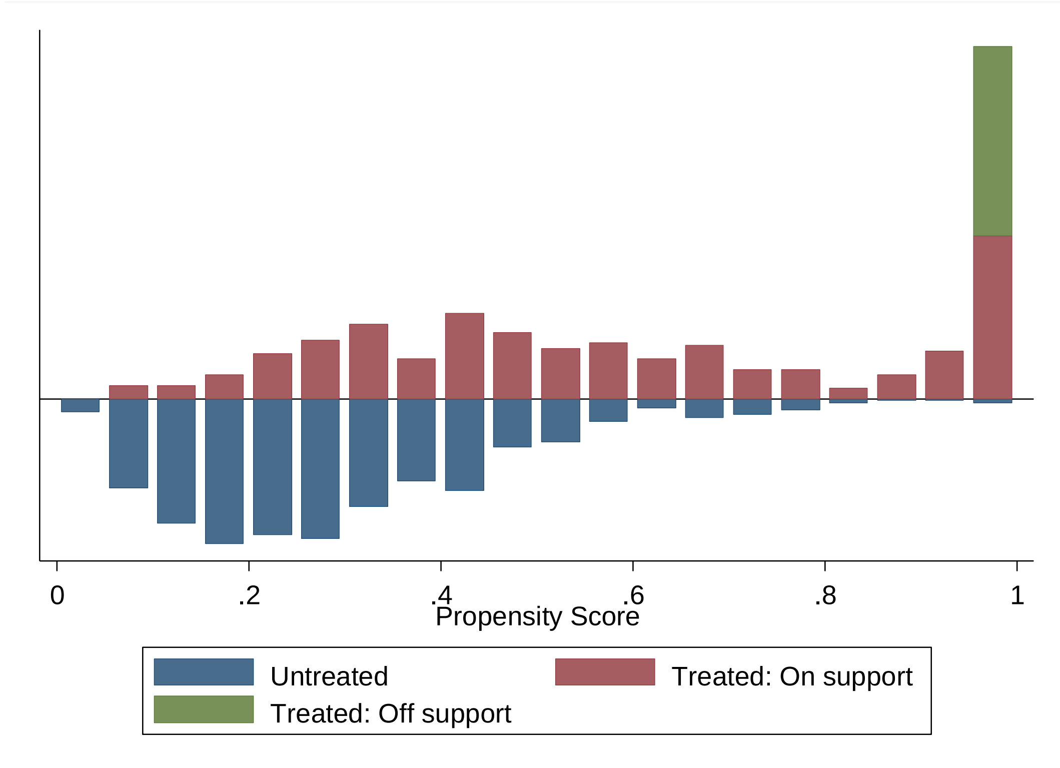

Figure B1. Common support condition for PSM model

The test for common support in DRF follows Hirano and Imbens (2004). The sample is divided in two groups using quintiles. Then GPS values are evaluated at the group median of the treatment variable (years of MFG). That is, the GPS values of group I are evaluated at the group's median of duration of MFG, and then the distribution of evaluated GPS values are plotted against the distribution of GPS values for group II sample. By examining the overlap of these two distributions one can identify the common support condition graphically. The same procedure is repeated for group II. Finally, the matched subsample is comprised of those individuals who are comparable across the two groups simultaneously. That is, individuals whose GPS is not among the common support region are dropped.

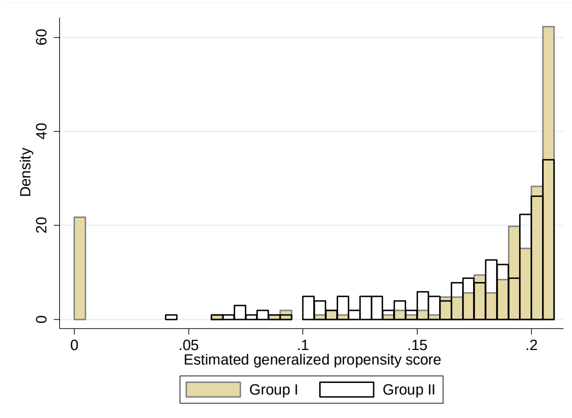

Figure B2a. Common support condition for DRF before deleting non-overlap for farmers in group I on those in group II.

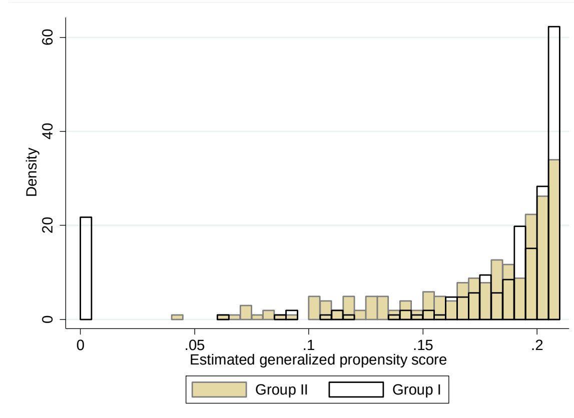

Figure B2b. Common support condition for DRF before deleting non-overlap for farmers in group II on those in group I

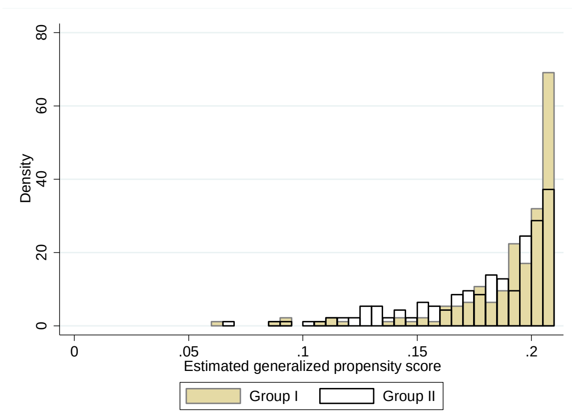

Figure B2c. Common support condition for DRF after deleting non-overlap for farmers in group I on those in group II.

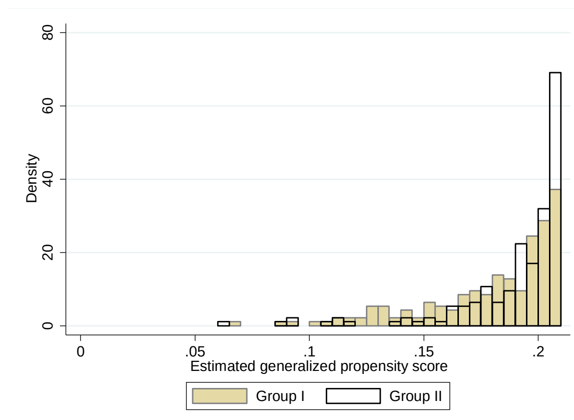

Figure B2d. Common support condition for DRF after deleting non-overlap for farmers in group II on those in group I