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Improving the speed of adoption of agricultural technologies and farm performance through farmer groups: evidence from the Great Lakes region of Africa

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Abstract

The article examines the effect of membership in farmer groups (MFG) on adoption lag of agricultural technologies and farm performance in Burundi, the Democratic Republic of Congo and Rwanda. We use duration and stochastic production frontier models on farm household data. We find that the longer the duration of MFG, the shorter the adoption lag and much more so if combined with extension service delivery. 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 the means through which improved farm performance can be achieved.

JEL classifications: O12, Q12, Q16

Keywords: Adoption lag; Farm performance; Farmer groups

1. Introduction

Farmer groups are progressively becoming an essential channel for the rural poor households to improve their income levels and achieve food security through improving crop productivity. They facilitate easy access to rural credit and input markets (Abebaw and Haile, 2013; Ashby et al., 2009; Uaiene et al., 2009), expedite efficient information flow on availability of improved agricultural technologies (Shiferaw et al., 2011), provide less costly networks to achieve successful dissemination and adoption of agricultural technologies (Bernard and Spielman, 2009), reduce both farmers' risk aversion toward new technologies and income shocks through collective risk management (Hogeland, 2006; Menapace et al., 2012; Pingali et al., 2005), and accelerate transitioning from smallholder subsistence farming into commercial oriented farming through collective marketing and value addition (Fischer and Qaim, 2012; Okello et al., 2007).[1] All these services provided through farmer groups are hardly contentious in empirical literature as key drivers of change in agricultural productivity (Hazell and Wood, 2008), especially in sub-Saharan African countries. Furthermore, participation in farmer groups has been associated with increased household income (Fischer and Qaim, 2012) and improved food security (Larsen and Lilleør, 2014; Vuthy et al., 2014). To date, however, we still know little about the role of membership in farmer groups (MFG) in reducing the waiting time to adopt

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

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agricultural technologies.[2] 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 article examines the role of MFG in reducing farmers' waiting time to adopt agricultural technologies and improve farm performance.

There is a large body of literature on farmers' adoption behavior of agricultural technologies and the factors explaining the variation in this behavior (Doss, 2006; Feder et al., 1985), but the literature explaining variation in the farmers' behavior to discontinue the waiting time to adopt technologies is still growing (examples include Abebe and Bekele, 2015; Burton et al., 2003; Dadi et al., 2004; Matuschke and Qaim, 2008). In the former case, the role of MFG in this literature is mixed: Some studies show that MFG enhances adoption of agricultural technologies (Abebaw and Haile, 2013; Fischer and Qaim, 2012; Kassie et al., 2011; Kristjanson et al., 2005; Wollni et al., 2010), and others indicate otherwise (Alene and Manyong, 2007; Herath and Takeya, 2003; Nkamleu and Manyong, 2005; Shiferaw et al., 2009; Wendland and Sills, 2008).

Away from technology adoption, studies investigating the effect of MFG on farm performance are also limited and with mixed results. 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 (2008) find that in Ethiopia, all else fixed, being a member of a 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 farmer group that provided agricultural technical assistance to other farmers. Second, MFG has been used as one of the determinants of technical efficiency across farms, and its effect on farm performance 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., 2014), while it had ambiguous effects on technical efficiency in coffee production in Costa Rica (Wollni and Brümmer, 2012).

This article contributes to the literature in two ways. First, the effect of MFG on adoption of agricultural technologies is evaluated through the time farmers with MFG take to adopt a particular technology compared to those without MFG. The following hypothesis is tested: The longer the farmer holds MFG together with access to extension services, the shorter the waiting time to switch from traditional to improved agricultural technologies. A flexible parametric proportional-hazards approach is used to test this hypothesis. Second, to resolve the mixed effects of MFG on farm performance, a nonmonotonic inefficiency model of Wang (2002) is used. This model has the ability to determine, within the sample, whether MFG has both positive and negative effects on technical efficiency. Here, we test the following hypothesis: Having MFG jointly with access to extension services leads to higher farm performance than having either MFG or access to extension service alone. We demonstrate that long duration of MFG significantly reduces the adoption lag and improves farm performance conditional on having access to extension service. We provide this evidence using farm household data collected from Burundi, the Democratic Republic of Congo (DRC), and Rwanda.

[2] The waiting time to adopt agricultural technologies and adoption lag are used interchangeably.

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 article, duration analysis models the farmers' decision to adopt improved agricultural technologies at some point after the farmer started active and independent farming,[3] where the waiting time to adoption (adoption lag) is defined as the number of years between the farmer's first exposure to the possibility ("risk") of adoption and the actual adoption. The year the household head started active farming and making independent production decisions is chosen as the initial exposure to the risk of adoption.[4] The survey tool included a question asking the farmers to determine their farming experience. Farming experience was defined as the number of years the household head had been engaged in farming, that is, starting from the year since he/she started making independent farming decisions.

The empirical model to estimate the probability of discontinuing the waiting time to adopt technologies after the farmer joined active and independent farming follows the hazard rate function (Wooldridge, 2010), and is represented as

$$\log(t) = \delta_m MFG + \delta_w + \sigma\xi, \tag{1}$$

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

[3] The MFG information was collected for both the household head and spouse.

[4] As expected, however, there are some households that had not yet adopted at the time of data collection. In the 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.

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 article implements a stochastic production frontier model that has the ability to accommodate "environmental factors" in both the production frontier and technical inefficiency functions (Coelli et al., 1999). Environmental factors include physical, managerial and farm organizational characteristics of the farmer. The empirical stochastic production frontier model is given as

$$\ln\ y_i = \alpha_0 + \sum_{j=1}^{3} \alpha_j \ln x_i + \frac{1}{2} \sum_{j=1}^{3} \sum_{k=1}^{3} \alpha_{jk} \ln x_{ij} \ln x_{ik} + \alpha_m MFG + \frac{1}{2} \alpha_{mj} MFG_i^2 + v_i - u_i, \quad (2)$$

where $u_i = z_i \beta + \varepsilon_i$,

ln is a 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 nonnegative technical inefficiency,[5] which can be explained by a vector of independent variables z_i (with MFG_i included), α_0, α_j, α_m, α_{mj}, β, and α_{jk} are parameters to be estimated, and ε_i is the error term.

Equation (2) was estimated using the nonmonotonic 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:

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

The estimation challenge faced, however, is correct identification of both Eqs. (1) and (2). 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., 2014). This leads to sample selection bias since those households in accessible locations are, by study design, selected. Second, wealth status and social capital influence the farmers' decision to participate in farmer groups. Evidence shows that wealthy individuals are less likely to participate in farmer groups (Abate et al., 2014; Bernard et al., 2008), but social capital enhances participation in and performance of farmer groups (Ruben and Heras, 2012). To overcome these challenges, the data we use in analysis were collected based on the sampling procedure that attempted to control for sample selection bias (see details in Section 3.1). The sampling procedure was clustered into two groups: Intervention sites that received technologies and control sites that were not exposed to technologies. Selection of both sites was based on having similar agro-ecological conditions, population pressure, and general location characteristics (Macharia et al., 2012).

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

The major limitation of PSM approach is that it does not control for unobservable heterogeneity that may influence the decision to participate in farmer groups. However, Imbens (2004) demonstrates—on the basis of PSM approach—that unobserved heterogeneity that affects participation in the program is independent of the outcome. We, thus, assume that the distributions of unobserved heterogeneity are the same for members and nonmembers of farmer groups. With PSM unable to test this assumption, we utilize the Rosenbaum bounds sensitivity analysis (Rosenbaum, 2002) to estimate how severe the unobserved heterogeneity that is correlated with both MFG and the speed of technology adoption would need to be to affect selection into participation in farmer groups in order to nullify the results. The Rosenbaum bounds sensitivity analysis calculates Wilcoxon sign rank test that gives upper and lower bounds of significance levels at particular levels of unobserved heterogeneity (DiPrete and Gangl, 2004). The presence of unobserved selection bias is tested within a range of gamma (Γ) values—established by the analyst—with the null hypothesis of no unobserved heterogeneity holding at $\Gamma = 1$ (Becker and Caliendo, 2007; Rosenbaum, 2002).

We attempt to overcome the limitation of PSM approach in two ways. First, in the estimation of Eqs. (1) and (2), we include country dummies to control for possible country-level fixed effects that may influence formation of farmer groups.[6]

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

[6] Although the intervention areas were selected based on having similar conditions (such as market access, population pressure, presence of development partners among other factors (Macharia et al., 2012), there are considerable

Second, since there may be correlation among farmers within farmer groups, we cluster standard errors at the farmer group level, and use robust standard errors (i.e., Eq. (1)).

An 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 farmer 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 whose supply may be dependent on the duration of MFG. The benefits can include easy access to inputs, agricultural training, credit services, 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 matching (GPSM) that has properties similar to those 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. For more details on implementation of the DRF, an interested reader is referred to Bia and Mattei (2008).

3. Data sources

The data were collected from farm households in Burundi, Eastern of DRC, and Rwanda by the Consortium for Improving Agriculture-Based Livelihoods in Central Africa (CIALCA) in 2011. The consortium comprised of International Institute of Tropical Agriculture (IITA), Bioversity International, and International Center for Tropical Agriculture (CIAT). CIALCA's main task was to improve crop productivity through dissemination of agricultural technologies to overcome the effects of the civil conflict that had disrupted food production and exacerbated rural poverty in central African countries (see Macharia et al., 2012, for details).

Data collection followed a multistage sampling procedure to randomly select a total of 913 farm households from both intervention and control villages (Macharia et al., 2012).[7] 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 participating in farmer groups. The estimation procedure and results from the probit model are reported in Appendix A (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 2010: Burundi (1,300), DRC (900), and Rwanda (600).

Important to note in Table 1 is the comparisons between matched and unmatched farmers in terms of their observed characteristics. Results show that before matching farmers having MFG with those without MFG based on their characteristics, there are significant differences between the two groups, in terms of education of the household head, household size, access to extension and training services, labor use, farm assets, and membership in other associations. The significant differences are expected since farmers were not selected from the same population and villages, although as earlier mentioned, the sampling of villages was based on having similar characteristics. However, after conducting the PSM process, significant differences persist in observed access to extension and training services between members and nonmembers of farmer groups. These differences in access to extension and training services conditional on having MFG underscore the basis for testing the stated hypotheses in Section 1. That is, we analyze the heterogeneity in reducing the adoption lag conditional on a farmer having access to extension and training services vis-à-vis having MFG. This analysis is done in Section 4.2.

3.1. Farmers' MFG and sources of technologies

CIALCA targeted farmers organized in groups, and whose main objective promoted improvement of agricultural productivity or collective marketing. With the aim of reducing on the transaction costs associated with technology dissemination, CIALCA identified these groups with the help of local partner organizations. That is, CIALCA used already existing farmer groups. The sample data used in the analysis involved 46% of surveyed farmers who had membership in farming oriented groups (Fig. 1). Some farmers also had membership in other groups not targeted by CIALCA. Table 1 also reports some farmers or other household members with multiple memberships in different groups.

In some areas, CIALCA provided the technologies and trainings directly to farmers and in other areas, the technologies 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 and improved

differences across the study countries in terms of, for example, governmental support programs, market development and agricultural policies.

[7] 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.

Table 1 Q4

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

	Members of farmer groups ($N = 420$)		Unmatched nonmembers of farmer groups ($N = 493$)		Matched nonmembers 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	0.809	0.021
Head with formal education (0/1)	0.750	0.021	0.688	0.021**	0.769	0.023
Household size (persons)	6.09	0.12	5.63	0.11***	6.00	0.13
Head's main occupation is farming (0/1)	0.893	0.015	0.886	0.014	0.893	0.017
Number of food insecure months in a year	3.05	0.08	3.08	0.08	3.03	0.08
Distance from home to nearest market (km)	4.08	0.33	4.14	0.32	4.36	0.42
Annual # of visits by government extension agents	2.50	0.24	2.35	0.25	2.44	0.29
Annual # of visits by NGO extension agents	3.08	0.22	1.06	0.11***	1.43	0.15***
Household received CIALCA training (0/1)	0.39	0.02	0.10	0.01***	0.12	0.02***
Total land operated (ha)	1.68	0.30	1.90	0.27	1.50	0.26
Labor used in crop production (person days)	86.80	4.24	63.06	2.93***	71.05	3.79
Amount of fertilizers applied (kg)[a]	362.80	40.93	286.77	48.53	336.84	67.75
Value of farm assets (US$)	2559.9	149.2	1921.8	241.1**	2186.7	174.7
Off-farm income per adult equivalent (US$)	29.93	8.42	269.0	225.3	357.3	335.6
Farm income per adult equivalent (US$)	76.30	9.15	81.74	16.51	75.52	12.42
Amount of credit received (US$)	17.08	3.57	13.32	3.89	17.08	5.43
Value of crop production per ha (US$)	535.1 [364]	63.8	599.3 [420]	68.9	729 [301]	88.6
Other household member(s) with membership in other groups apart from farmer groups (0/1)	0.295	0.022	0.264	0.02	0.288	0.024
Head's membership in other groups apart from farmer groups	0.645	0.024	0.509	0.023***	0.605	0.026

Figures in square brackets are numbers of observations that differ from the overall sample size.
***, **, * are significance levels at 1%, 5%, and 10%, respectively.
[a]Here and throughout the article, the amount of fertilizer refers to total amount of organic (dry form) and inorganic fertilizers used.

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 and cake). 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.

Fig. 2 reports different sources of technologies among farmers who were engaged in production of CIALCA mandate crops. The figure reports information on key providers of new technologies including government extension programs (GOV'T), CIALCA, and nongovernmental organizations extension programs (NGO). For farmers who have ever used or were using improved technologies, Fig. 2 reports that a fairly good number of them sourced technologies from CIALCA and government extension agents while 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 through farmer groups. Our sample data show that only one farmer received improved cassava technologies from a government extension agent through a farmer group and another one received same technologies from an NGO extension agent through a farmer group. 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 that farmer groups play in improving adoption of agricultural technologies.

4. Estimation of the main results

4.1. Determinants of adoption lag of agricultural technologies

Table 2 reports two sets of results from the duration analysis using Eq. (1). The upper panel reports results from the

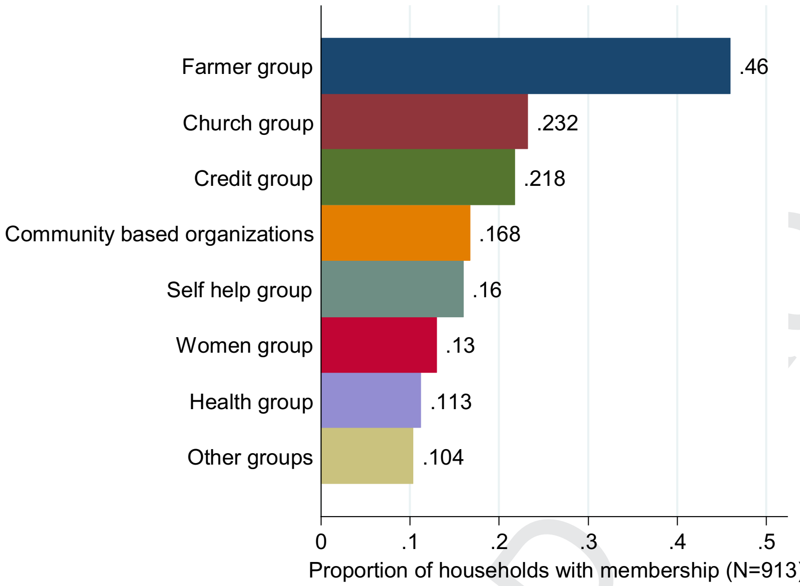

Fig. 1. Farmers' membership in groups.

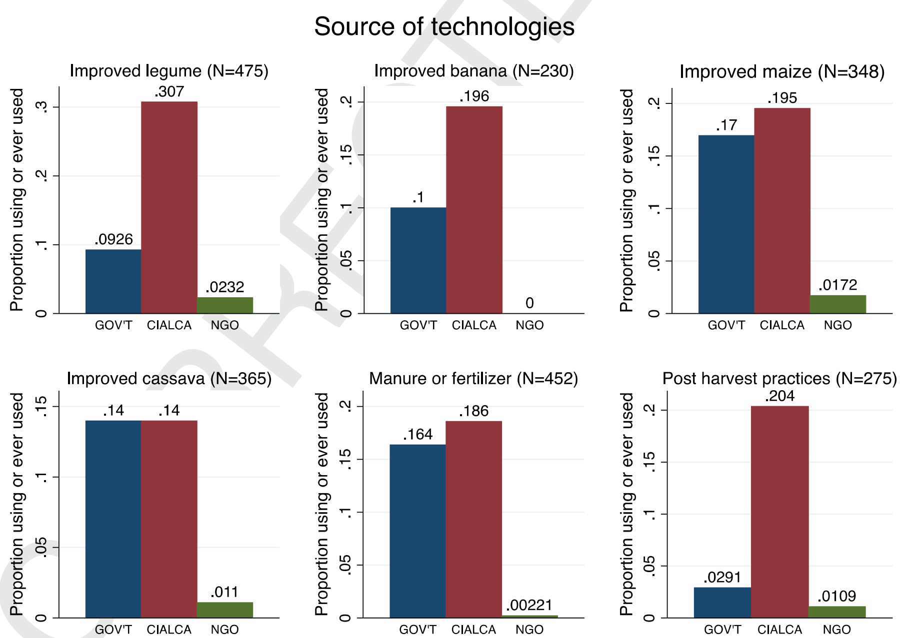

Fig. 2. Source of improved technologies used by participating farmers.

subsample obtained through PSM, while the bottom panel reports results obtained using GPSM that involves a subsample of farmers with MFG only. To save space, only results obtained from the matched subsamples using PSM and GPSM approaches and variables of interest are reported. Results from unmatched sample are relegated to Appendix A (Table A3). Full results with all explanatory variables are available from the authors on request. Household characteristics included in the estimations but excluded from Table 2 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 GPSM are reported in Appendix B (Figs. B1 and B2). The figures show that the common support assumption holds. As aforementioned,

Table 2
Determinants of adoption lag of agricultural technologies

PSM subsample	Improved legumes	Improved banana	Improved maize	Improved cassava	Use of fertilizer	Post-harvest
MFG (0/1)	−0.143***	−0.017	0.030	0.005	−0.229***	0.006
	(0.026)	(0.017)	(0.036)	(0.034)	(0.065)	(0.007)
Number of visits by GEA[a]	0.009**	0.006	0.030***	0.006	0.006	0.004
	(0.003)	(0.007)	(0.009)	(0.008)	(0.006)	(0.006)
Number of visits by NEA[b]	−0.035***	−0.036***	−0.042***	−0.034***	−0.036**	−0.031**
	(0.010)	(0.004)	(0.001)	(0.005)	(0.012)	(0.014)
Received CIALCA training (0/1)	−0.260**	−0.124***	−0.263***	−0.198*	−0.017	−0.202*
	(0.109)	(0.027)	(0.044)	(0.121)	(0.251)	(0.105)
Other household characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Constant	−6.570***	−6.778***	−7.166***	−7.255***	−6.714***	−6.346***
	(0.369)	(0.272)	(0.958)	(0.637)	(0.645)	(0.154)
Log likelihood	−465.226	−449.308	−338.468	−403.655	−418.067	−492.848
Average adoption lag (years)	20.759 (0.584)	22.128 (0.622)	21.148 (0.672)	22.484 (0.627)	20.806 (0.615)	22.235 (0.591)
Number of observations	565	499	412	480	516	523
GPSM subsample						
MFG (years)	−0.045*	−0.033**	−0.033*	−0.066**	−0.047**	−0.066***
	(0.026)	(0.015)	(0.020)	(0.026)	(0.023)	(0.017)
Number of visits by GEA[a]	0.009	−0.021	0.040**	−0.013	0.006	−0.006
	(0.027)	(0.025)	(0.017)	(0.021)	(0.017)	(0.017)
Number of visits by NEA[b]	−0.044**	−0.033**	−0.047**	−0.030*	−0.008	−0.019
	(0.020)	(0.017)	(0.020)	(0.017)	(0.015)	(0.013)
Received CIALCA training (0/1)	−0.414**	−0.077	−0.321*	−0.269*	−0.338**	−0.223*
	(0.174)	(0.130)	(0.176)	(0.151)	(0.171)	(0.129)
Other household characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Constant	−5.974***	−7.089***	−6.351***	−6.041***	−5.363***	−5.793***
	(0.710)	(0.602)	(0.758)	(0.701)	(0.709)	(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.
[a]GEA—government extension agents.
[b]NEA—nongovernment extension agents.

PSM does not control for unobserved heterogeneity, but we utilize the Rosenbaum bounds sensitivity analysis to detect its presence. Considering the duration time to adopt technologies as an outcome variable, we estimated the Rosenbaum bounds for each of the considered technologies and all results yielded the same effects. For this study, we only reported results from a sensitivity analysis considering all technologies combined, and used the average duration time to adopt technologies as an outcome variable. Table A2 reports the results, and given that MFG expectedly reduces adoption lag, the upper bounds—under the assumption that MFG effects have been overestimated—are less important (Becker and Caliendo, 2007) and are also not reported. The results show that we fail to reject the null hypothesis that unobserved heterogeneity associated with MFG has significant effect on the adoption lag. That is, the gamma value of $\Gamma = 1$ is not significantly different from zero. The unobserved heterogeneity can only pause a significant effect when Γ doubles or is higher. This suggests that if there is an unobserved heterogeneity that causes the odds ratio of self-selection to be two times or higher for farmers with MFG, this heterogeneity would have a significant effect on the speed of technology adoption.

In interpreting the estimates in Table 2, we multiply the coefficient by 100 to obtain semi-elasticity of covariates. A negative (positive) coefficient means a shorter (longer) length of waiting time to adopt agricultural technologies. In other words, a positive (negative) coefficient indicates a higher (lower) probability of adopting agricultural technologies.

The results indicate that being a member of a farmer group associated with CIALCA reduced the time lag to adopt improved legumes and use of fertilizer (organic and inorganic) by about 14% and 23%, respectively, *ceteris paribus*. That is, having MFG and jointly receiving the agricultural extension or training service increases the chances of discontinuing the waiting time to adopt some agricultural technologies. In addition, 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.

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 fertilizer	Post-harvest
MFG (0/1)	-0.089^{***}	0.043^{**}	0.007	0.039	-0.271^{***}	-0.012
	(0.000)	(0.014)	(0.033)	(0.040)	(0.069)	(0.009)
Number of visits by GEA[a]	0.012^{***}	0.013^{***}	0.026^{***}	0.015^{***}	0.009	0.013^{**}
	(0.000)	(0.003)	(0.004)	(0.004)	(0.009)	(0.004)
Number of visits by NEA[b]	-0.022^{**}	-0.027^{***}	-0.041^{***}	-0.039^{***}	-0.054^{***}	-0.061^{***}
	(0.009)	(0.003)	(0.003)	(0.000)	(0.004)	(0.010)
Received CIALCA training (0/1)	-0.261^{**}	-0.125^{***}	-0.263^{***}	-0.199^{*}	-0.020	-0.226^{**}
	(0.110)	(0.024)	(0.043)	(0.119)	(0.256)	(0.111)
Interaction between MFG and number of visits by GEA	-0.010^{***}	-0.018^{**}	0.010^{***}	-0.025^{***}	-0.004^{*}	-0.025^{***}
	(0.000)	(0.006)	(0.002)	(0.001)	(0.002)	(0.002)
Interaction between MFG and number of visits by NEA	-0.018^{*}	-0.011^{*}	-0.003	0.011^{***}	0.028^{***}	0.046^{***}
	(0.010)	(0.006)	(0.005)	(0.000)	(0.007)	(0.007)
Other household characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-6.599^{***}	-6.814^{***}	-7.146^{***}	-7.299^{***}	-6.711^{***}	-6.333^{***}
	(0.354)	(0.311)	(0.981)	(0.605)	(0.663)	(0.165)
Log likelihood	−465.012	−448.926	−338.385	−403.246	−417.806	−491.256
Number of observations	565	499	412	480	516	523

Figures in parentheses are standard errors.
***, **, * are significance levels at 1%, 5%, and 10%, respectively.
[a]GEA—government extension agents.
[b]NEA—nongovernment extension agents.

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 exist 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—holding other factors fixed—reduced the time lag to adopt improved legumes, banana, maize, and cassava varieties, use of fertilizer, and improved post-harvest technologies by 3–7%.

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 extension 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 the agricultural technology adoption 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).

4.2. *Adoption lag and interaction effects between MFG and providers of extension services*

The negative and significant estimates of MFG, number of visits by NGO extension agents, and access to CIALCA training suggest that these nonstate 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 obtained using the PSM subsample. It should be noted that we do not interact participation in farmer groups with CIALCA in the upper panel of Table 3, because the interaction is already in-built since CIALCA disseminated technologies through farmer groups. The presence of a significant interaction term indicates that the effect of MFG on the adoption lag is different at different values of the diverse sources of extension services. The nonsignificant interaction term means that the effect of MFG on the adoption lag does not depend on access to extension services.

In general, results show significant interactive effects between MFG and access to different sources of extension services on adoption lag. On the one hand, the results further support the evidence that early adoption of considered technologies occurred among farmers with MFG who received CIALCA extension services, compared to their cohorts who received extension services from other sources. On the other hand, coefficients on the interaction terms, MFG × GEA and MFG × NEA had both negative and positive effects on adoption lag. Specifically, early adoption of improved legumes, use of fertilizer 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, they adopted improved legume and banana

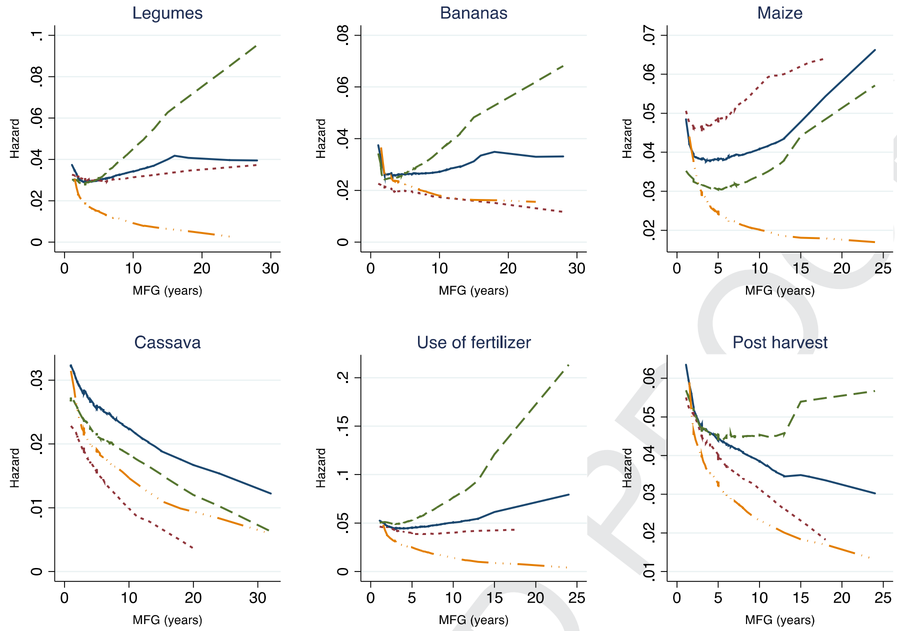

Fig. 3. The probability of discontinuing waiting time to adopt technologies plotted against the length of MFG. The solid line plots the effects of MFG alone, the dashed line plots interaction effects between MFG and NGO extension services, the dotted line plots the interaction effects between MFG and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

varieties, but delayed adoption of improved cassava varieties, use of fertilizer and post-harvest technologies.

Similar to PSM subsample analysis with interactions, we interacted years of MFG with access to CIALCA training to test heterogeneity associated with duration of MFG using the GPSM subsample. That is, the subsample of farmers with MFG only. The results—not reported but available on request—show that 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 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 or NGO extension services or vice versa for farmers at different duration periods 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. Interpretation becomes more complicated when one 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 farmers who only 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 (Fig. 3).

The solid curve (Fig. 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 farmers receiving extension services from government programs to make early decisions to adopt improved banana and cassava varieties, and post-harvest technologies. In the study areas, bananas are a major food and income source and can hence ensure food and cash income; cassava is a food security crop because it is more resilient to weather patterns and it stores as a tuber in the soil, and post-harvest technologies guarantee both food security and value addition (Macharia et al., 2012). Our findings are consistent with the notion that farmers prioritize adoption of technologies that ensure food security and cash income (Maiangwa et al., 2010), especially if the technologies are disseminated along with delivery of extension or training services. For example, government extension services delivered through farmer groups have been found to improve both food security (Wendland and Sills, 2008; Fisher and Lewin, 2013) and in some cases, crop income (Okoboi et al., 2013). This is because government extension programs, unlike NGO

Table 4
Effects of source of technology on adoption lag

	Improved legumes	Improved banana	Improved maize	Improved cassava	Use of fertilizer	Post-harvest
MFG (0/1)	−0.001	−0.043	0.055	0.024	−0.014	−0.006
	(0.002)	(0.029)	(0.035)	(0.029)	(0.024)	(0.036)
GEA as source of technology (0/1)	−1.478***	−14.738***	−16.007***	−16.695***	−1.524***	−16.745***
	(0.031)	(1.409)	(1.376)	(1.460)	(0.066)	(1.144)
NGO as source of technology (0/1)	−15.181***	§	−15.921***	−15.987***	−11.110***	−0.085
	(1.357)		(1.303)	(1.371)	(1.579)	(1.567)
CIALCA as source of technology (0/1)	−3.346***	−2.400***	−3.436***	−16.362***	−3.628***	−16.602***
	(0.349)	(0.142)	(0.512)	(1.288)	(0.077)	(1.173)
Interaction between GEA and MFG	−14.440***	12.805***	−0.024	0.215	0.211***	0.096
	(1.438)	(1.423)	(2.058)	(2.116)	(0.040)	(1.666)
Interaction between NEA and MFG	−0.804	§	0.283	−0.582	§§	−16.566***
	(1.903)		(1.955)	(1.960)		(2.748)
Other household characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Constant	−6.733***	−6.877***	−7.295***	−7.444***	−6.990***	−6.423***
	(0.212)	(0.230)	(0.953)	(0.504)	(0.213)	(0.204)
Log likelihood	−414.205	−431.468	−300.946	−366.448	−383.918	−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.
§There were no farmers who sourced banana plantlets from NGO extension system (see Fig. 2).
§§Only one farmer sourced fertilizer from NGO extension system. The variable was dropped because of collinearity (see Fig. 2).

programs that are often time bound, have the ability to sustain extension information delivery, which reduces uncertainty surrounding adoption of agricultural technologies (Rivera and Alex, 2004; Rivera and Qamar, 2003).

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. There is evidence to show that where extension programs have built capacity of the local community, there has been high and sustained rates of adoption of technologies in contrast to programs that do not involve local capacity building (Krishnan and Patnam, 2013; Pan et al., 2015). Second, CIALCA used a farmer-participatory approach to disseminate technologies. This approach allowed farmers to evaluate and select appropriate technologies suitable for their resources. Evidence shows that farmer participatory research enhances adoption of agricultural technologies through social networks (Takahashi et al., 2015). Third, CIALCA disseminated technologies through farmer groups. Farmer groups play an important role in knowledge and information management and sharing through regular meetings in which they determine information that is important to them (Maiangwa et al., 2010). 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 service delivery conditional on having 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. On the one hand, results show that all sources of technologies (CIALCA, government and NGO extension systems) significantly reduce the waiting time to adopt technologies. On the other hand, 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 × MFG) and post-harvest technologies (NEA × 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.

4.4. Farm performance and MFG

This section shows how MFG affects farm performance in terms of technical efficiency and its marginal effect on farm productivity. Tables 5 and 6 report the summary statistics of technical efficiency levels and marginal effects estimated from

Table 5
Average technical efficiency by source of extension service

	Unmatched sample			PSM sample			GPSM sample		
	Farmer did not participate in . . .[a]	Farmer participated in . . .	Difference in means	Farmer did not participate in . . .	Farmer participated in . . .	Difference in means	Farmer did not participate in . . .	Farmer participated in . . .	Difference in means
All households	0.448 (0.223) [776]	–	–	0.503 (0.221) [362]	–	–	0.540 (0.241) [362]	–	–
Farmer groups (FG)	0.407 (0.233) [414]	0.495 (0.200) [362]	-0.088^{***}	0.472 (0.224) [296]	0.533 (0.214) [295]	-0.061^{***}	–	–	–
CIALCA training	0.420 (0.223) [583]	0.532 (0.199) [193]	-0.112^{***}	0.480 (0.222) [428]	0.564 (0.207) [163]	-0.084^{***}	0.518 (0.242) [211]	0.570 (0.237) [151]	-0.052^{**}
GOV'T extension services (GES)	0.430 (0.235) [395]	0.467 (0.207) [381]	-0.037^{***}	0.501 (0.223) [302]	0.504 (0.219) [289]	−0.003	–	–	–
FG and GES	0.503 (0.187) [170]	0.488 (0.211) [192]	0.0160	0.534 (0.207) [146]	0.533 (0.221) [149]	0.001	0.566 (0.227) [170]	0.517 (0.252) [192]	0.050^{**}
NGO extension services (NES)	0.401 (0.220) [403]	0.498 (0.214) [373]	-0.097^{***}	0.476 (0.220) [288]	0.528 (0.219) [303]	-0.052^{**}	–	–	–
FG and NES	0.480 (0.188) [128]	0.503 (0.206) [234]	−0.024	0.515 (0.215) [117]	0.546 (0.212) [178]	−0.031	0.546 (0.223) [128]	0.537 (0.251) [234]	0.009

***, **, * are significance levels at 1%, 5%, and 10%, respectively. Figures in parentheses are standard deviations and those in square brackets are numbers of observations.
Note that technical efficiency levels of GPSM sample are not categorized by farmer groups since the sample considers members of farmer groups only.
[a]The " . . . " refers to categories listed in the first column.

Eqs. (2) and (3), respectively. Full results of the stochastic production frontier model and technical inefficiency shifters are reported in Tables A5 and A6.

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. The results show that there is a statistically weak significant U-shaped relationship between crop productivity and the duration of MFG, but MFG significantly reduces the technical inefficiencies in crop production (Table A5). 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 values (*P*-values) were 5.26 (0.072), 6.93 (0.031), and 0.10 (0.949) for unmatched, PSM, and GPSM samples, respectively. The results reflect failure to accept the null hypothesis in the unmatched and PSM samples, but not in the GPSM samples.

Table 5 reports average technical efficiency levels for unmatched, PSM, and GPSM samples. Our discussion follows the results obtained from the PSM sample since it compares farmers with and without MFG, but have similar observed characteristics. The estimates in Table 5 show that the average technical efficiency is about half of the potential farm productivity, implying that a 50% 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 having MFG are about 6% more efficient than those without. Similarly, farmers who received extension services from CIALCA and NGOs were 8% and 5% more efficient in improving their productivity, respectively, than those who did not receive these services.

To further understand the relationship between farm performance and MFG, we plotted technical efficiency levels against MFG (Fig. 4, left panel). The plot shows a nonlinear 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 into 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 are enthusiastic about using new technologies to produce toward the frontier output level. As time passes however, the technical efficiency improves at a decreasing rate up to about 15 years of MFG, beyond which technical efficiency declines gradually with more time of MFG, possibly due to diminishing returns as-

Table 6
Average marginal effects of MFG and number of extension visits

Marginal effects	Unmatched sample ($N = 776$)	PSM sample ($N = 591$)	GPSM sample ($N = 362$)
Average length of MFG (years)	-0.066^{***}	-0.0780^{***}	-0.070^{***}
	(0.005)	(0.005)	(0.006)
Average number of visits by government extension agents	-0.063^{***}	-0.009^{***}	0.0319^{***}
	(0.004)	(0.002)	(0.003)
Average number of visits by NGO extension agents	-0.153^{***}	-0.068^{***}	0.005^{***}
	(0.008)	(0.004)	(0.001)

***, **, * are significance levels at 1%, 5%, and 10%, respectively. Figures in parentheses are standard errors. The significance levels for marginal effects are bias-corrected and bootstrapped with 1,000 replications.

sociated with lengthy MFG. This finding underscores the mixed relationships between crop productivity and MFG documented in literature (Davis et al., 2012; Mwaura, 2014). It is generally argued in this literature that despite MFG having positive effects on adoption of new technologies, there might be heterogeneous effects associated with the duration of MFG that may lead to inefficiencies in some crops. However, the same literature falls short of controlling for nonmonotonic effects, and hence assumes linear relationship between technical efficiency and duration of MFG.

The results in Table 6 further highlight the importance of MFG and extension services on technical inefficiency. The discussion is based on the PSM sample for the reasons mentioned earlier. The overall average marginal effect of MFG on technical inefficiency is –0.078, suggesting an increase in farm level output by 7.8% for every additional year of membership. The average marginal effects of extension delivery from government and NGOs are –0.009 and –0.068, respectively, and translate into corresponding increases in farm-level output by 0.9% and 6.8%. However, Table 6 reports averages of marginal effects but not their ranges and how they vary with the length of MFG. To visually demonstrate this and relate it to MFG, the right panel of Fig. 4 plots the marginal effects of MFG and extension visits on the length of MFG. 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 analyzes the effect of MFG on the farmers' time lag to adopt agricultural technologies and farm performance using duration analysis and nonmonotonic inefficiency effects models, respectively. The findings indicate that member farmers are more likely to be early adopters of agricultural technologies than nonmembers. However, this early adoption depends

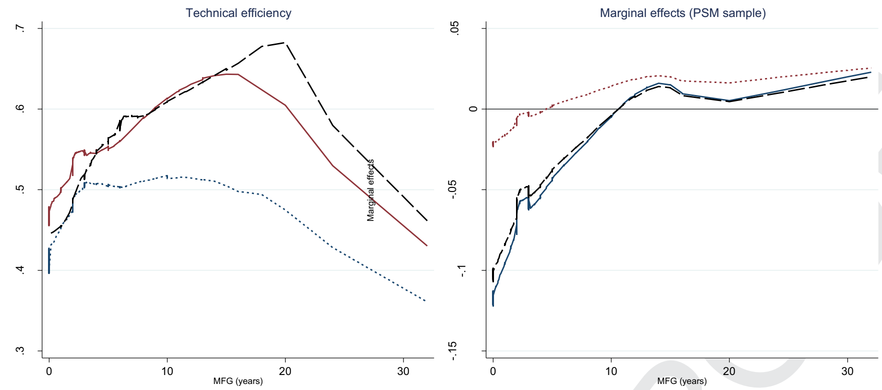

Fig. 4. The nonparametric prediction of technical efficiency and marginal effects on the length of MFG. For the technical efficiency plot, the dotted line represents unmatched sample, the solid line represents PSM sample, and the dashed line represents GPSM sample. Regarding marginal effect plots, the plots show PSM sample marginal effects of MFG (solid line), government extension delivery (dotted line), and NGO extension delivery (dashed line) on the length of MFG. Plots for unmatched and GPSM sample marginal effects are not reported to save space.

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 enhancing inputs (inorganic 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 lags similar to those of 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 nonmembers to join or to retain MFG, combined with incentives to improve nongovernmental 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 5% and as much as 8% 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 only be lower.

An important finding in the case of Great Lakes region of Africa is that MFG has nonmonotonic effects on technical inefficiency, that is, during the initial years of MFG, the marginal effect 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 a number of ways. First, 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. Second, 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 third, development of a dissemination and extension strategy that ensures sustainable service delivery to enhance adoption of technologies.

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Appendix A

Participation in farmer groups

The existing literature (see, e.g., Abate et al., 2014; Bernard et al., 2008; Fischer and Qaim, 2012; Shiferaw et al., 2011) guided the selection of factors that influence farmer's decision to participate in farmer groups. However, some of the factors are potentially endogenous. In particular, farm income may be partially determined by MFG if the groups provide services like input credit. The provision of credit by farmer groups makes credit potentially endogenous if it is entered as an independent variable. The other source of endogeneity bias is inclusion of—as an explanatory—the other household members with MFG apart from the household head. For example, if a household member joins a farmer group before the household head does and this member starts enjoying the benefits of membership such as receiving credit, then the household head may be incentivized to join the group also. Since the participation in farmer groups—the dependent variable—is based on the decision of the decision of the household head, the situation such as one described in this example would lead to endogenous decision-making. However, of 145 other household members that had MFG in addition to the household head, only four of them had joined farmer groups before their household heads. We assume that this number of four members is too small to bias our estimates. We therefore only treated farm income and credit as endogenous variables.

To test whether farm income and credit are endogenous in the farmer-group participation model, we use a two-stage control function (Papke and Wooldridge, 2008). The first stage involves Q5
regressing, separately, farm income and credit on exclusion restriction variable(s) and other variables that may include those used in estimating the farmer-group participation model. The exclusion restriction variable refers to the variable that directly affects farm income or credit but does not have direct impact on participation in farmer groups. We used, as exclusion restriction variable, the ratio of protein consumption to consumption of other nonprotein foods. The survey tool collected information on consumption of various foods including staple crop foods and nonstaple foods like meat, eggs, milk products, fruits, and vegetables. The protein ratio was computed by summing up the amount of food from protein source foods and dividing the sum by the total amount of food consumed from nonprotein source foods. Since protein source foods include some staple crops (like soybeans) and nonstaple foods (like meats), the higher the ratio the higher the probability of purchasing food (or the higher

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 a year previous to the survey	0.022 (0.020)
Number of squared contacts with government extension agent in a year previous to the survey	−0.001 (0.001)
Number of contacts with NGO agent in a year previous to the survey	0.178^{***} (0.032)
Number of squared contacts with NGO agent in a year previous to the survey	-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 in 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 R^2	0.3059
Number of observations	903

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

Table A2
Rosenbaum bounds sensitivity analysis

Critical value of unobserved heterogeneity (Γ)	*t*-value
1	−1.288
2	5.167
3	8.917
4	11.500
5	13.500
6	15.000
7	16.250
8	17.333
9	18.292
10	19.167

Table A3
Determinants of adoption lag of agricultural technologies using unmatched sample

Participation in farmer groups (0/1)	Improved legumes	Improved banana	Improved maize	Improved cassava	Use of fertilizer	Post-harvest
MFG (0/1)	−0.151**	−0.037***	−0.013	−0.013	−0.194***	−0.021
	(0.063)	(0.011)	(0.057)	(0.048)	(0.058)	(0.029)
Number of visits by GEA[a]	−0.003**	−0.005	0.013**	−0.008	−0.002	−0.002
	(0.001)	(0.004)	(0.006)	(0.006)	(0.004)	(0.005)
Number of visits by NEA[a]	−0.026**	−0.030***	−0.036***	−0.029***	−0.015	−0.027**
	(0.012)	(0.005)	(0.006)	(0.001)	(0.011)	(0.009)
Received CIALCA training (0/1)	−0.415***	−0.166***	−0.345***	−0.272**	−0.174	−0.285***
	(0.049)	(0.009)	(0.082)	(0.117)	(0.267)	(0.055)
Other household characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Constant	−6.501***	−6.654***	−7.021***	−6.875***	−6.554***	−6.128***
	(0.079)	(0.444)	(0.377)	(0.260)	(0.522)	(0.002)
Log likelihood	−625.571	−603.256	−454.884	−562.666	−550.040	−661.382
Number of observations	733	647	542	633	651	675
Duration in farmer groups (years)						
MFG (years)	−0.024	−0.026**	−0.026*	−0.034**	−0.027*	−0.045***
	(0.016)	(0.010)	(0.014)	(0.017)	(0.014)	(0.013)
Number of visits by GEA[a]	0.009	−0.017	0.037**	−0.018	0.007	−0.008
	(0.021)	(0.021)	(0.017)	(0.019)	(0.014)	(0.015)
Number of visits by NEA[a]	−0.038**	−0.029*	−0.049**	−0.027*	−0.006	−0.015
	(0.018)	(0.015)	(0.019)	(0.015)	(0.014)	(0.012)
Received CIALCA training (0/1)	−0.466**	−0.141	−0.369**	−0.335**	−0.408**	−0.257**
	(0.162)	(0.123)	(0.165)	(0.140)	(0.157)	(0.120)
Other household characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Constant	−6.279***	−7.186***	−6.367***	−6.438***	−6.002***	−5.973***
	(0.624)	(0.558)	(0.689)	(0.645)	(0.674)	(0.505)
Log likelihood	−279.640	−265.135	−222.552	−260.271	−255.513	−297.830
Number of observations	371	322	271	313	333	331

Figures in parentheses are standard errors.
***, **, * are significance levels at 1%, 5%, and 10%, respectively.
[a]GEA—government extension agents, [b]NEA—nongovernment extension agents.

Table A4
Adoption lag and the interaction between MFG and providers of extension services using unmatched sample

Participation in farmer groups (0/1)	Improved legumes	Improved banana	Improved maize	Improved cassava	Use of fertilizer	Post-harvest
MFG (0/1)	−0.117***	0.014***	−0.027	0.029	−0.240***	−0.023
	(0.029)	(0.002)	(0.038)	(0.031)	(0.052)	(0.037)
Number of visits by GEA[a]	−0.004**	−0.002	0.010***	−0.002***	−0.001	0.005**
	(0.001)	(0.002)	(0.001)	(0.001)	(0.003)	(0.002)
Number of visits by NEA[b]	−0.011***	−0.020***	−0.027***	−0.028***	−0.035***	−0.049***
	(0.003)	(0.002)	(0.007)	(0.002)	(0.003)	(0.010)
Received CIALCA training (0/1)	−0.410***	−0.164***	−0.344***	−0.268**	−0.174	−0.296***
	(0.050)	(0.007)	(0.085)	(0.119)	(0.273)	(0.058)
Interaction between MFG and number of visits by GEA	0.003	−0.013***	0.015	−0.022**	−0.003	−0.021***
	(0.008)	(0.002)	(0.010)	(0.007)	(0.008)	(0.004)
Interaction between MFG and number of visits by NEA	−0.024***	−0.012***	−0.016	0.002***	0.028***	0.033***
	(0.001)	(0.003)	(0.012)	(0.000)	(0.005)	(0.009)
Other household characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Constant	−6.508***	−6.683***	−6.992***	−6.915***	−6.549***	−6.135***
	(0.088)	(0.471)	(0.419)	(0.245)	(0.543)	(0.005)
Log likelihood	−625.313	−602.952	−454.622	−562.277	−549.701	−660.210
Number of observations	733	647	542	633	651	675

Figures in parentheses are standard errors.
***, **, * are significance levels at 1%, 5%, and 10%, respectively.
[a]GEA - government extension agents, [b]NEA - nongovernment extension agents.

Table A5
Frontier production function

	Unmatched	PSM matched	GPS matched
Log of operated area (ha)	−2.084*** (0.524)	−1.598** (0.687)	−1.416** (0.609)
Log of farm labor supply (person days)	−0.319 (0.431)	−0.947* (0.512)	−1.023** (0.504)
Log of fertilizer and manure (kg)	−0.455*** (0.121)	−0.508*** (0.142)	−0.424** (0.170)
Log of farm related assets (US$)	−0.147 (0.184)	−0.543** (0.252)	−0.109 (0.205)
Log of operated area squared	0.272** (0.135)	0.533*** (0.206)	0.165 (0.183)
Operated area and labor interaction	−0.052 (0.105)	−0.352** (0.163)	−0.117 (0.163)
Operated area and fertilizer/manure interaction	−0.040 (0.029)	−0.072* (0.039)	−0.013 (0.049)
Operated area and farm assets interaction	0.057 (0.058)	0.140* (0.080)	−0.007 (0.078)
Log of labor supply squared	0.082 (0.109)	0.138 (0.133)	0.169 (0.103)
Labor and fertilizer/manure interaction	0.086*** (0.023)	0.066** (0.027)	0.102*** (0.028)
Labor and farm assets interaction	0.008 (0.039)	0.095* (0.052)	0.059 (0.056)
Fertilizer and manure squared	0.027 (0.023)	0.045* (0.025)	0.036 (0.029)
Fertilizer/manure and farm assets interaction	0.004 (0.012)	0.018 (0.015)	−0.014 (0.019)
Farm related assets squared	0.009 (0.023)	−0.005 (0.028)	−0.013 (0.025)
Log of length of MFG (years)	−0.482* (0.247)	−0.420 (0.257)	−0.169 (0.549)
Log of length of MFG squared	0.329 (0.247)	0.148 (0.257)	0.093 (0.420)
Constant	8.636*** (1.142)	11.361*** (1.473)	9.402*** (1.448)
Number of observations	776	591	362

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

Table A6
Determinants of technical inefficiency

	Unmatched	PSM matched	GPS matched
Membership in farmer groups (years)	−0.664* (0.375)	−0.582** (0.289)	0.240** (0.112)
Annual # of visits by government extension agent	−0.531** (0.269)	−0.197 (0.217)	−0.147* (0.076)
Annual # of visits by NGO extension agent	−1.141** (0.499)	−0.510 (0.438)	0.066 (0.052)
Distance from home to nearest market (km)	−0.307** (0.149)	−0.298 (0.415)	−1.130* (0.668)
Head with formal education (0/1)	−0.400 (0.793)	8.233 (8.878)	−1.247** (0.489)
Household owned radio, phone or television (0/1)	−0.868 (0.813)	−0.396 (0.737)	4.504*** (1.748)
Number of food insecure months in a year	0.056 (0.222)	0.107 (0.304)	0.597*** (0.152)
Household size (persons)	−0.218 (0.164)	−0.390** (0.189)	−1.006*** (0.335)
Log of land owned (ha)	0.563 (0.502)	0.438 (0.443)	0.582 (0.553)
Log of off-farm income per adult equivalent (US$)	−1.014** (0.478)	−1.006 (0.683)	−0.147 (0.212)
Amount of credit received (US$)	−0.591 (0.461)	−0.413 (0.403)	−0.587 (0.361)
Other household member(s) with MFG apart from household head (0/1)	−1.722 (2.304)	1.181 (0.955)	−1.427 (1.360)
Country effects (Burundi compared to DRC)	1.000 (0.786)	2.116*** (0.816)	5.463*** (1.896)
Country effects (Rwanda compared to DRC)	−3.793 (2.765)	−4.469 (4.289)	1.353 (1.085)
Constant	4.034*** (1.357)	−4.731 (9.400)	−3.084 (2.002)
Number of observations	776	591	362

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

the value of consumption). Protein sources include foodstuffs that may not necessarily be produced on farm or if they are produced on farm the market value attached to them is relatively higher than the one attached to other nonprotein foodstuffs.[8] One would expect this protein ratio to have a direct effect on the farm income and credit, but to indirectly affect participation in farmer groups through changes in farm income and credit. As expected, the coefficients (standard error) on the protein ratio –0.004 (0.002) and –0.009 (0.002) in the separate regressions for farm income and credit, respectively, are significantly different from zero, although the former is weakly significant at 10% level. The protein ratio was not significant when we included it in the farmer-group participation model supporting the validity of our exclusion restriction in our sample. Other explanatory variables included in each of the regressions are same as those reported in Table A1 except MFG variables. We then predicted residuals from each of the regressions to be used in second stage. Full results are available from the authors on request.

[8] Considering median values that are less influenced by outlier prices that may be obtained by farmers accessing distant and better markets, the farm gate prices for legume crops (protein source foods) were relatively higher than those for other crops. The average (median) farm gate prices per kg for considered crops were: ground nuts, US$ 3.2(1.7); beans, US$ 0.62(0.43); soybean, US$ 0.75(0.50); bananas, US$1.1(0.36); maize, US$ 0.25(0.25); and cassava, US$ 0.85(0.25).

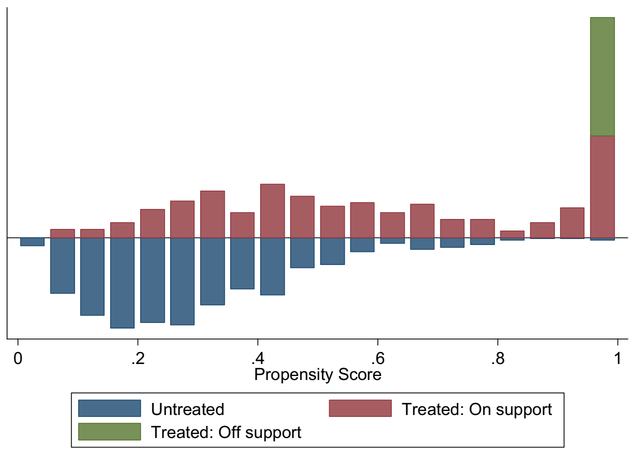

Fig. B1. Common support condition for PSM model.

In the second stage, the farmer-group participation model is estimated with residuals from the first stage included as additional explanatory variables. The test for endogeneity of farm income and credit is obtained as a *t*-test on the coefficients of the residuals. The test results show that the residuals are statistically not different from zero, suggesting that farm income and credit are not endogenously determined in the household decision making to participate in farmer groups. We, thus, estimated the farmer-group participation model ignoring the first-stage estimation.

Appendix B

The test for common support in DRF follows Hirano and Imbens (2004). The sample is divided into two groups using quintiles. Then generalized propensity score (GPS) values are evaluated at the group's 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

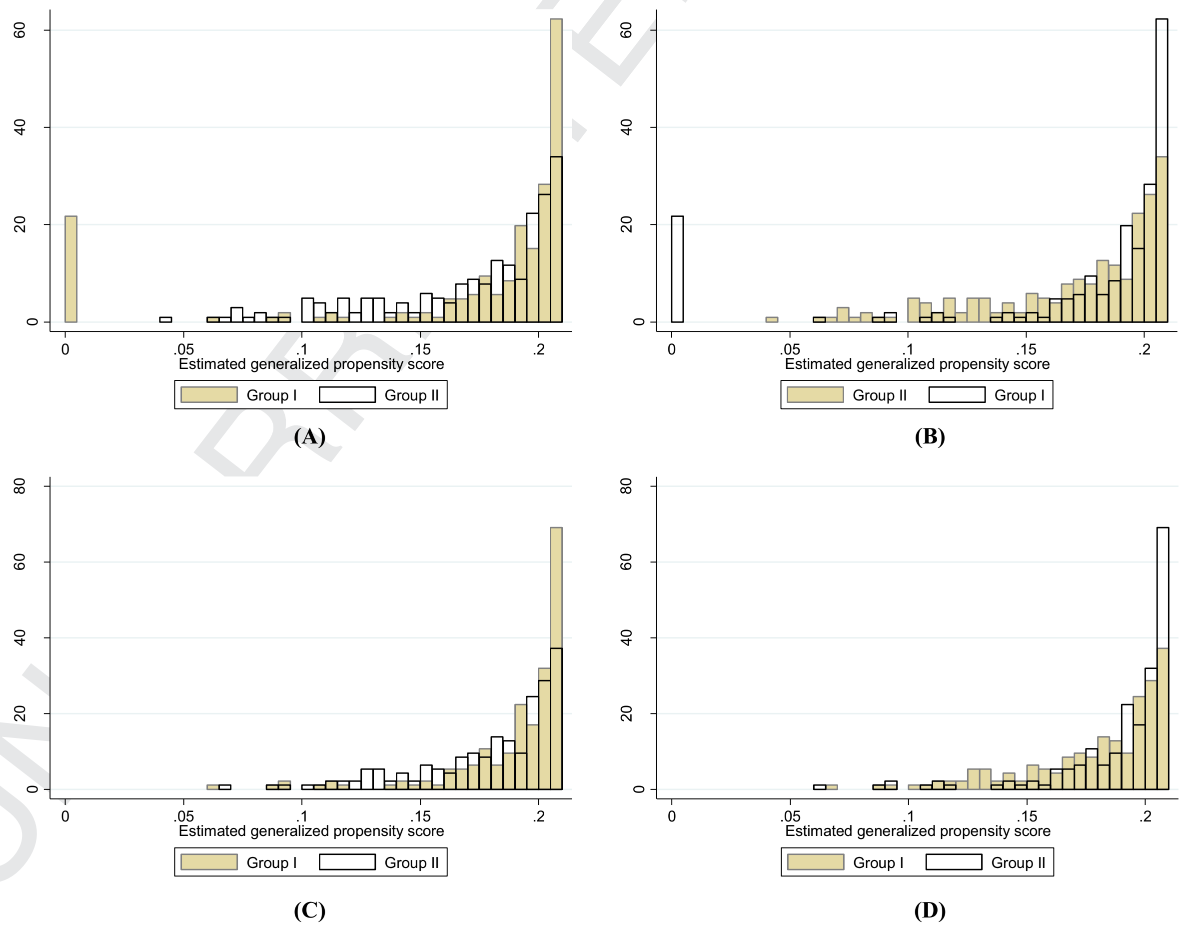

Fig. B2. (A) Common support condition for DRF before deleting non–overlap for farmers in group I on those in group II. (B) Common support condition for DRF before deleting non–overlap for farmers in group II on those in group I. (C) Common support condition for DRF after deleting non–overlap for farmers in group I on those in group II. (D) Common support condition for DRF after deleting non–overlap for farmers in group II on those in group I.

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.

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