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Influence of membership to farmer association on maize yields in Bungoma County: A propensity score matching analysis

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ABSTRACT

Limited access to extension services, credit facilities, inputs, and markets are important causes for declining food production in sub-Saharan Africa (SSA). Farmer associations could be pertinent in solving some of these constraints, for instance, in the provision of extension services, credit, and marketing of farmers' crops. However, there is a paucity of empirical evidence on the performance of farmer groups in disseminating technologies and information. This study investigated the influence of belonging to a farmer association on a farmer's maize yield and income among smallholder farmers in Bungoma County. The study employed a descriptive survey design to collect data from the farmers. The target population was all the 498 members of Bungoma Small-Scale Farmers Forum farmer associations who were the experimental group and a similar number of neighbouring farmers who were non-members which formed the control group. Simple random sampling was used to select the 223 respondents. Propensity score matching was used to minimize selection bias. Farmer associations were dominated by younger, more educated and female members. The average treatment effect (ATT) for yield and maize income was 325 Kg/ha (z=3.45, p=0.001) and Kshs 15 814 (z=2.46, p=0.014), respectively, showing that membership of farmer associations had a significant influence on the farmers' maize yield and income. The study recommends that farmer associations and other cooperative movements should be increased and strengthened in order to boost farmers' crop yields and incomes by the agriculture department of the county goverment.

Keywords: Farmer association, propensity score matching, maize yield and income

INTRODUCTION

The central causes for declining food production in SSA are land degradation through soil fertility depletion and a lack of an enabling socio-economic environment, for instance limited access to credit facilities, inputs, markets, and extension information (Sanchez *et al*., 2009; Nandwa, 2003). Kenya's extension service, much like that of other countries in SSA, has gone through many changes since its original inception through the colonial government, in response to the changing social, environmental, and political settings. Recently, reductions in government services and ineffective and inappropriate extension approaches have led to gaps in extension of technologies to small-scale farmers, who play a major role in the Kenyan economy (Gautam, 2000). Most rural farms in Kenya are diverse, on average they are less than two hectares of land, and are characterized by limited resources (Moris, 1991). This causes particular problems to extension and other service providers, who typically make blanket extension recommendations based on technologies designed for larger, more modern and homogenous farms. Farming in rural areas is more often a means of achieving a livelihood rather than as a business. Although often ignored by government and other policy makers, these small-farm livelihood systems are home to about

80% of Kenyans, are an important source of rural employment, and contribute significantly to agricultural production (Government of Kenya, 2010). For instance, smallholders produce 70% of Kenya's maize, 65% of the coffee, 50% of the tea, 80% of the milk, 70% of the beef, 100% of pyrethrum, and many of the food crops (Muturi, 2001).

Farmer groups or associations (FA) could be germane in catalyzing the provision of extension services to farmers. Within a group context, one resource person can be trained, who will then be empowered to pass on the information to the group. Because they have similar circumstances, usually speak the same mother tongue and have comparable educational backgrounds, farmer extension officers can communicate well with and are trusted by fellow members. Farmer extensionists are able to reach more people in a timelierfashion than regular agents can (Nyakuni, 2001). Groups are believed to extend technologies faster than individual farmers do and have also been found to support fellow members in adoption (Phiri *et al*., 2004). They are valuable as a form of collective action to farmers, providing resources such as credit, labor and information. Groups allow farmers to obtain new technologies, benefit from economies of scale, enter into stable relationships with suppliers, and set rules for natural resource management (Place *et al*., 2002). Farmer groups can be facilitated to network with other groups, forming strong farmers' associations and giving farmers a voice with which to educate other farmers and to demand services.

The importance of groups in knowledge dispersion has been investigated in other countries. In Australia, Andreata (2000) found in her study of farmer groups that they were an efficient way for farmers to share information and experience. Women's groups were shown in Malawi to reach more smallholders than customary extension practices, and to be an efficient way to reach women farmers (Sigman *et al*., 1994). Geran (1996) found that group formation in Zimbabwe led to increased links with service providers.

Within Kenya, informal self-help groups have historically been an important tool of community development. The colonial government used these groups to help promote soil conservation, and formed the Department of Community Development to organize such groups in 1948 (Wellard and Copestake, 1993). Following independence, the harambee (Swahili word synonymous with let us all work together) movement brought about more group formation in order to obtain government assistance. Place *et al*. (2002) found that in central Kenya most adults belonged to groups. The major source of agroforestry germplasm in Kenya was other farmers (relatives and neighbors), according to Edouard (1998). Members belonging to a Kenyan group, specializing in dairy goat in Meru and Tharaka Nithi were found to benefit from dissemination of information and technologies, especially at the buck stations (Mutia, 1999). Alawy (1998) found that women in Kenya feel that they benefit from being in the group through training, cash, financial assistance, knowledge gained, and food.

However, membership to groups does not always guarantee access to services. Alawy (1998) in a study on the Kenyan coast found that extension services tended to be biased towards male farmers, Christians and 'up-country' tribes as compared to female farmers, Muslims, and local tribes. This was likely to occur because the extension workers were mostly male, Christians working in a Moslem area, and from an 'up-country' tribe. Parkins (1997) in a study on the mechanisms of group extension of agroforestry technologies in central Kenya found that the success of networking varies by gender, attitude toward participation and recency of migration. Farmer groups lack the power or authority to institute or regulate policy as governments do. They may lack capacity, resources and the infrastructure that government or private organizations have (Ssemakula and Mutinda, 2011). Many researchers are advocating community-based extension through farmer groups as a means of scaling up technologies (Ssemakula and Mutinda, 2011 Nyakuni, 2001; Raussen, Ebong and Musiime, 2001; Wambugu, Franzel, Tuwei & Karanja, 2001). However, there is limited extant empirical evidence on the performance of farmer groups in disseminating technologies and information (Pretty & Ward, 2001). The objective of the study was to establish the effect of belonging to a farmer association on a farmer's maize yield and income among smallholder farmers in Bungoma County.

METHODOLOGY

The study was carried out in Bungoma County, located in the Western region of Kenya. Occurring at an altitude of 1 385 metres, the geographical coordinates of the county are 0^0 34' 0" North and 34^0 34' 0" East. The county experiences a bimodal rainfall distribution with long rains from February to late august, ranging from 1000mm to 2000mm whereas the soils are a variety of nitisols, ferralsols and acrisols [Government of Kenya (GOK), 2014]. This study employed a descriptive survey design, which enabled it to obtain requisite information from a large segment of small-holder farmers over a short period. The target population was 996 farmers (498 members of Bungoma Small-Scale Farmers Forum farmer associations and a similar number of neighbouring farmers who were non-members). Sampling both members and non-members of farmer associations was crucial to allow comparison of farmer maize incomes between the two groups. This study collected data from 223 farmers, according to the formula and correction for sampling from small population outlined in (Montgomery, 1997; Kothari, 2004), who were selected by simple random sampling. Field study was conducted between June and August of 2015. Data was collected using structured interviews, administered by the researcher and three trained enumerators.

This study required a comparison of maize yields and incomes of farmer association members and non-members, in order to determine the effect of membership to FA on a farmer's income. The major constraint in causal inference studies is the construction of the counterfactual outcome, that is, what would have happened to participants in absence of treatment (Dehejia and Wahba, 2002). In the context of this study, the basic question thus is, "what would have been the income for those farmers belonging to FA had they not belonged to FA"? Formally, let Y1 be the maize yield and income when a farmer *i* belongs to a FA (P =1) and Y0 be the same variable when one is not a member (P=0). Thus, the expected (E) treatment effect for a treated population (the so called 'average treatment effect on the treated or ATT') can be (Caliendo and Kopeinig, 2005) written as:

$$T_{ATT} = E(T \mid P = 1) = E(Y1 \mid P = 1) - E(Y0 \mid P = 1) \qquad (1)$$

As the counterfactual mean for those belonging to FA, the term, E (Y0 | P=1, is not observed and one must choose an appropriate substitute for it in order to estimate ATT. One possibility is to use the mean outcome of untreated individuals (farmers who are not members of FA), E (Y0 | P=0. In this case, the ATT can be estimated as follows:

$$T_{ATT} = E(Y1 \mid P = 1) - E(Y0 \mid P = 0) \qquad (2)$$

Directly inferring ATT by equation (2) in an observational study such as this one could have been misleading, because the treatment group (members of FA) and the comparison group (FA non-members) may have been a non-random sample. If factors that influence the treatment participation decision (membership of FA) also affect the outcome (maize yield and income), using E (Y0 | P=0 as a substitute for E (Y0 | P=1 will introduce systematic bias (Chaouani, 2010). Covariates in this study, for instance, farmers' county of residence, maize acreage, and biographical variables (such as gender, age, and education) have been found to simultaneously influence membership of FA and crop yield and income (Odendo *et al*., 2010). Thus, maize yields and incomes of famers in the two groups would differ even in the absence of treatment leading to the so-called selection bias. Since it was not possible to assign randomly households to treatment (membership to FA) and control (non-membership) groups, as the study was observational, FA members and non-members were matched on observed characteristics differentially distributed in the two groups in order to make them more similar. The primary assumption underlying matching methods is the conditional independence assumption (CIA), also referred to as "ignorable treatment assignment" (Rosenbaum and Rubin, 1983) or "selection on observables" (Heckman and Robb, 1985), which implies that the treatment (that is, membership to FA) is random conditional on some set of observed covariates (X). In notation,

$$(Y = 0, Y = 1) \perp P \mid X \qquad (3)$$

Where X is a vector of farmer ex-ante covariates, and $\perp$ denotes independence. In addition, matching also requires the condition of common support or overlap, which rules out the phenomenon of perfect predictability of P given X:

$$0 < Prob.(P = 1 \mid X) < 1 \qquad (4)$$

This condition ensures that persons with the same X values have a positive probability of being both participants and non-participants (Caliendo and Kopeinig, 2005). Assuming CIA and common support holds the ATT can then be estimated as follows:

$$ATT = E(Y1 \mid X, P = 1) - E(Y0 \mid X, P = 0) \qquad (5)$$

Where ATT is computed as the mean difference in outcomes over the common support. With increasing number of covariates, the application of matching methods becomes difficult to implement. To overcome this problem, this study adopted the use of propensity score matching (PSM), proposed by Rosenbaum and Rubin (1983), which reduced a multidimensional matching problem to a one-dimensional problem. A propensity score *P(X)* is defined as the probability of receiving treatment (in this context, membership of a FA) conditional on X. Thus,

$$P(X) = Prob.(P = 1 \mid X) \qquad (6)$$

The ATT can then be computed by averaging the conditional effect over the propensity score distribution in the treated group. In notation,

$$T_{ATT}^{PSM} = E_{p(X)\mid P=1}\{E[Y1 \mid P = 1, P(X)] - E[Y0 \mid P = 1, P(X)]\} \qquad (7)$$

The covariates to be used in the calculation of propensity scores should be ones that simultaneously influence the outcome variable (in this study, maize yield and income) and participation decision (membership of FA or otherwise) (Caliendo and Kopeinig, 2005). The theorized covariates in this study were the farmer's gender (male or female), age in years, education (those with none, primary and secondary or post-secondary education).

Others were farm size in acres, presence of off-farm income (yes or otherwise), ownership of title to land (yes or otherwise), and number of dependants. Binary logistic regression and ordinary least squares (OLS) regression were used to determine whether the covariates influenced the participation decision and outcome variables, respectively. Differences amongst members of FA and non-members were analyzed using chi- square (χ^2) cross tabulations (for categorical data) and t-tests (continuous variables).

The steps of PSM in this study were as follows: (1) calculation of the propensity scores using a probit model, (2) Each observation of the treated group (members of a farmer organisation) was matched with control group observations (non-members) based on their propensity score. For matching, several methods including nearest neighbour with replacement, nearest neighbour without replacement and Kernel matching were used and the best matching method, in terms of bias reduction was chosen, (3) After matching, *t*-tests were conducted to determine whether matching was able to reduce bias and to see whether the means for the conditioning variables differed between treated and control units, and (4) To evaluate the effect of membership of a farmer association on maize yield and income, the ATT were calculated. Testing the statistical significance of treatment effects and computing their standard errors was conducted using the bootstrapping method to account for the additional variance due to estimation of the propensity scores and the imputation of the common support (Chaouani, 2010).

All statistical tests were performed with the aid of STATA statistical package, version 12. Significant levels were measured at 95% confidence level with significant differences recorded at $p < .05$.

RESULTS AND DISCUSSION

Household's farmer characteristics

Table 1 presents household characteristics of the farmers, segregated according to membership of FA or otherwise.

Farmer associations were dominated by female members (76.0%) compared to male members (24%). These results corresponds to that of Nyakuni (2001) and Davis (2008) who found that female farmers were likely to join groups among subsistence producers. In most cases, farmers join common interest groups (CIGs) to better meet the needs of their households where they contribute most labour.

Non-members of farmer associations were found to be significantly older (mean age, 53 years) compared to members (mean age, 51). Age is an important factor that influenced the demand for new technologies. Joining farmer associations increases chances of farmers to improving their production through enhancing access to technologies and pooling of resources. Members were also found to be better educated (30% had secondary or post-secondary education and 10% had no formal education) relative to non-members (21% had secondary or post-secondary while 16% had no formal education). The combination of younger age and more education meant that the members were likely to be more progressive compared to their non-member counterparts (Odendo *et al.*, 2010). Members of the associations were generally more endowed with significantly larger pieces of land (3.13 acres) compared to non-members (2.02 acres). Members and non-members were found not to significantly differ (at p<.05) with respect to ownership of title deeds, percentage of households with off-farm incomes, off-farm activities, and the number of dependants

Table 1: Sample household characteristics of members and non-member farmers in Bungoma

Characteristics	Non-members (n=92)	Members (n=131)	χ^2 or t-value
Respondents' gender (%)			57.58***
(1) Male	75.0	23.7	
(2) Female	25.0	76.3	
Mean age of household head (years)	53.15	51.08	2.08**
Farmer education (%)			2.79**
(1) Farmers with no formal education	16.1	10.3	
(2) Farmers with primary education	63.2	59.8	
(3) Farmers with secondary or post-secondary education (%)	20.7	29.9	
Mean farm size (acres)	2.02	3.13	-3.06***
Households with title to land (%)	34.8	31.3	0.30
Households with off-farm income (%)	37.8	39.5	0.07
Off-farm activities (% of farmers)			0.51
(1) Business	57.1	64.3	
(2) Employment	28.6	26.2	
(3) Others	14.3	9.5	
Mean number of dependants	6.71	7.08	-1.02
Mean number of dependants < 20 years	4.20	4.39	-0.56
Mean number of dependants (20-50years)	1.93	2.08	-0.82
Mean number of dependants > 50 years	0.83	0.79	0.36

*****, ** Significant at the one and five percent levels of probability, respectively by t test or $\chi 2$ test**

Propensity Score Matching Estimates

All the theorized factors significantly influenced maize yield and income except for presence of off-farm income, ownership of title to land and number of dependants. However, gender was the only covariate, which significantly influenced membership of FA, suggesting that the other factors were distributed independently amongst members and non-members. Consequently, farmers who were members in FA were matched with those who were non-members on the basis of propensity scores calculated according to the farmer's gender. Table 2 presents the parameters of propensity scores estimated by the probit model.

Table 2: Propensity Score Model Coefficient Estimates

Variables	**Coefficient**	**Standard error**	***z***	***p>z***
Intercept	-0.496	0.131	-3.78	p<.001
Gender	1.385	0.185	7.48	p<.001
Overall model evaluation				
Number of observations		223		
Log Likelihood		-121.175		
LR Chi2		59.94		
Prob> Chi2		p<.001		
Pseudo R2		0.198		

The coefficient for the conditioning variable gender was found to statistically significant (z=7.48, p<.001), showing that propensity scores were significantly different amongst member and non-member farmers. Since the coefficient for gender was positive (1.385), it implied that being female (female was coded as 0 while male was coded as 1 in the data) increased the log odds of belonging to a FA (propensity score) by 1.385.

Table 3 shows the descriptive statistics for the estimated propensity scores amongst members and non-members.

Table 3: Descriptive statistics of propensity scores on member and non – member farmers

Descriptive statistic	Members (n=131)	Non – members (n=92)
Mean	0 .6939	0.4357
Standard deviation	0.214	0 .219
Skewness	-1.239	1.155
Kurtosis	2.535	2.333

The mean of propensity scores was higher among members (0.6939), compared to non-members (0.4357) whereas the value of skewness was negative for members but positive for non-members. This showed that members had significantly higher propensity scores relative to non-members. Hence, it was important to match the propensity scores of member and non-member farmers to reduce bias. Of the three matching techniques, nearest neighbour with replacement, nearest neighbour without replacement and kernel matching, the latter was chosen as it reduced the most bias. This matching technique requires that all treated units are matched with a weighted average of all controls where weights are inversely proportional to the distance between the propensity scores of the treated and control groups (Rausen, 2001).

After matching, *t*-tests were conducted to determine whether matching was able to reduce bias and to see whether the means for the conditioning variable of gender differed between treated and control units. These results are presented in Table 4.

Table 4: Balancing Tests of Propensity Score Matching

Panel A: Mean tests (t-tests) and bias reduction							
Variable	Sample	Mean treated	Mean control	*t*	*p > t*	% Bias	% Bias reduction
Gender	Unmatched	0.76336	0.25	8.77	P<.001	119.1	
	Matched	0.76336	0.76336	-0.00	1.000	-0.0	100.0
Panel B: Overall Evaluation of balance							
	Pseudo R^2	LR chi^2	P > chi^2	Mean Bias	Median Bias		
Raw	0.198	59.94	P<.001	119.1	119.1		
Matched	-0.000	-0.00	1.000	0.0	0.0		

The mean for propensity scores calculated on the basis of gender in the unmatched sample was significantly greater in the treated group (members) (0.76336) compared to the control group (non-members) (0.25), t=8.77, p<.001. However, after matching, the means of the treated group (0.76336) and the control group (0.76336) were not significantly different (in fact, they were numerically equal), t = -0.00, p=1. This indicated that matching was very successful, managing to eliminate the differences in the propensity scores between the treated and control groups. Matching eliminated both mean and median bias from an initial 119.1% in the raw groups to 0.0% in the matched groups. Thus, matching reduced bias by 100%. Overall, matching removed variance (measured by Pseudo R^2) from 0.198 in the raw groups to 0.0 in the matched groups.

Estimation of the Treatment Effects

Table 5 presents the means of the outcome variables between member and non-member groups.

Table 5 Means of outcome variables for members and non-members.

Variable	Respondent type	Mean	Standard deviation
Maize yield (kgs/hectare)	Non-member	534.67	791.96
	Member	705.51	864.43
Maize income (Kshs)	Non-member	24417.57	42459.87
	Member	33780.76	82595.83

Maize yields and income were generally higher amongst farmers who were members of farmer association compared to those who were not. The standard deviations for both variables were also large (the standard deviation was larger than the mean), which indicated that there were wide variations in yield and income amongst both member and non-member farmers.

Table 6 shows the average treatment effect (ATT) for maize yield and income.

Table 6: Average treatment effect (ATT) of the outcome variables

Outcome variable	ATT	Bootstrap Standard error	*Z*	$p > z$
Maize yield (Kgs/hectare)	324.84	94.14	3.45	0.001
Maize income (Kshs)	15814.45	8079.25	2.46	0.014

The ATT for yield of maize and income was 325 Kg/ha and Kshs 15 814, respectively, and these were statistically significant. This showed that membership of a farmer association will on average increase the yield of maize and a farmer's income by 325 Kg and Kshs 15 814, respectively, over and above those for non-members. The FA in this study was found to be an important platform in the provision of extension services to farmers. Farmers in the association learned about new technologies, for instance, MBILI ('Managing Beneficial Interactions in Legume Intercrops'), Ua Kayongo (striga weed resistant maize), foliar feed use, 'push pull' (a strategy to control pests by using repellent 'push' and trap 'pull' plants). Others were 'lab lab' relay (intercrops with the second plant after the first has reached physiological maturity), liming, and use of fortified compost. In addition, farmers in the group worked together, visited each other's farms, shared experiences in group fora, and encouraged each other.

It was also observed during the interview that majority of the association members sold their products through the associations since most of them get inputs from the associations on credit. The group also owned go-downs where they could store members produce as they wait for the prices to improve. The higher yield among members of FA suggested that FA could be pertinent in enabling farmers to access new agricultural information and technologies through trainings that enable members increase their productivity. The benefits of group membership have been articulated in studies by, for instance, Ramisch *et al*. (2006) and Nkamleu (2007). In addition, the collective bargaining power for higher prices that the farmer association has when looking for markets for their members produce and also the elimination of middlemen by the association could have led to higher farm gate price margin. Farmers rely on information gained through interaction with peers, i.e. their own experience before they make important decisions. Members in associations have the added advantage of buying inputs collectively at cheaper prices and this enhances technology adoption. Moreover, an extension officer is able to reach more farmers in a group than individual farmers at given period (Odembo *et al.*, 2010).

CONCLUSION AND RECOMMENDATIONS

This study analysed the influence of belonging to a farmer association on a farmer's maize yield and income among smallholder farmers in Bungoma County using propensity score matching. The study found that membership of a farmer association on average significantly increase the yield of maize and a farmer's income by 325 Kg and Kshs 15 814, respectively, over and above those for non-members. This could arise from better dispersion of farming technologies and information amongst members, enhanced training, ability to obtain credit, collective marketing and bargaining, access to storage facilities, and elimination of middlemen.

The study recommends that FAs and other cooperative movements should be increased and strengthened in order to boost farmers' crop yields and incomes. It will be easy for extension officers to render services when farmers are in groups.

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