244- Drivers of Collective Action and the Welfare Gains of such Initiatives among smallholder farmers: Experiences from Kenya

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Abstract

This study assessed the determinants of participation and intensity of participation in collective action initiatives. It also examined the effect of participation in such initiatives on household commercialization and on household welfare (incomes). It uses a double hurdle approach (a logit regression model to examine the determinants of participation in collective action and a Poisson regression model to assess the factors that determine the intensity of participation). The study then tests the difference in mean incomes and commercialization between participants and non-participants. The study finds that farmer/household specific variables, farm specific variables, endowment variables and regional variables influence the decision to participate as well as the extent of participation in collective action initiatives. Results further indicate that there exist significant differences in output and input market participation (commercialization) and in mean incomes as a result of participation in collective action initiatives influence the decision to participate in collective action initiatives. The implication of these findings is that for collective action initiatives to be to be effective in achieve the desired goals of helping farmers commercialize, capacity of farmers (e.g. through trainings) to operate and manage them should be improved. Stronger linkages with other institutions like public institutions, credit institutions should be encouraged and fostered so as to address the needs of the farmers. The study discusses the implications of these findings for policy.

Key Words: Determinants, drivers, collective action, welfare, farmers, Kenya

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1. Introduction

Market access is one of the most important factors influencing the performance of smallholder agriculture in developing countries, and in particular least developed countries. Access to new and better-paying markets for agricultural products is vital in enhancing and diversifying the livelihoods of poor subsistence or semi-subsistence farmers. Farmer collective actions can potentially eliminate the market failures experienced by smallholder farmers in developing countries emanating from high transaction costs (Markelova et al. 2009). Farmer organizations/ groups can be engines for capacity building, information sharing, and innovation in rural areas (Bingen et al. 2003).

Social capital has been a matter of academic pursuit by different authors and touching on different aspects of the subject. Some studies try to identify determinants of participation in farmer organizations (such as La Ferrara 2002; Bernard and Spielman 2009) while others study on the impacts of group membership in terms of market access, prices, and income (such as Roy and Thorat 2008). Others still focus on organizational and institutional aspects of farmer groups, (such as Hellin et al. 2009; Narrod et al 2009).

An aspect that is important but has not been given the attention it deserves is the decision participation and intensity of participation in collective action initiatives. This research gap is the focus of this study. It is not enough just to model farmers' decision to participate in collective action initiative. Care must be taken to go a step further to model also the intensity of participation. This is intended to ascertain the more "active" verses the "passive" participants. In identifying these key determinants of intensity of participation, the factors that are crucial in group success are then highlighted. Only committed members will participate in group activities more often because to them they perceive the benefits of collective action to be more than the costs and vice versa. It is therefore important to gain understanding on the factors that contribute to high or low participation in collective action initiatives so as to predict and enhance group performance.

This study assesses the determinants of decision to participate as well as determinants of participation intensity in collective action initiatives in Kenya. Specifically, the study examines the number of years of participation in a group and the degree of market participation to assess individual commitment and contribution to shared goals. The rest of this paper is organized as follows: Section 2 presents the conceptual framework of the study. Section 3 presents the study results while Section 4 concludes.

2. Methodology

This section presents the empirical methods used in assessing the determinants of collective action initiatives as well as drivers of intensity of participation in collective action initiatives. The study area, sampling procedure and the data are also described in this section.

2.1. Empirical framework

2.1.1 Drivers of participation in collective action initiatives

Participation in collective action in this study is measured using a binary choice variable of "Yes" or "No" type indicating *participation* or *non-participation* by a farmer, respectively. Commonly used approaches for estimating such discrete dependent variable regression models are the Logit and Probit regression techniques (Liao, 1994; Maddala, 2001; Gujarati, 2004). These two approaches are quite similar and generate almost identical predicted probabilities Gujarati (2004). However, the difference between these two approaches is the nature of their distribution as captured by cumulative distribution function (CDF) with Probit having a normal distribution while Logit has a logistic distribution. The choice between Probit and Logit regression model depends, therefore, on the distribution assumption one makes. Logit model is usually preferred because its comparative mathematical simplicity and its convenience and flexibility when the predictor variables are a mix of continuous and categorical variables and/or when they are not normally distributed (Sirak & Rice, 1994). Some of the predictor variables in this study are categorical and therefore this study uses the binary Logit regression model to identify the drivers of market participation.

Following Maddala (2001), the probability, p, that a household participates in the market, is given by:

$$P = e^{z}/1+e^{Y} \qquad (1)$$

Central to the use of logistic regression is the Logit transformation of p given by Y

$$Y= ln\ (p/1-p) \qquad (2)$$

Where;

$$Y = Y\ (F, R, K, L) + \varepsilon \qquad (3)$$

Y is a latent variable that takes the value of 1 if the farmer participates in the market and 0 otherwise.

The vector $\boldsymbol{F}$ in Equation (3) represents farmer-specific characteristics, while $\boldsymbol{R}$ is a vector of farm-specific variables, $\boldsymbol{K}$ is a vector of capital endowments, $\boldsymbol{L}$ is a vector of location/district level characteristics and ε is the stochastic term assumed to have a logistic distribution. The empirical model estimated contains the following variables):

1) Farmer specific variables ($\boldsymbol{F}$) = log of age, gender, and occupation
2) Farm specific variables ($\boldsymbol{R}$) = distance to output market, number of crop enterprises, household size and distance to local market

3) Capital endowment variables (K): Physical asset (log of crop income, log of assets, log of land, use of ICT tool), human capital (education level, years of farming experience) and social capital (membership in collective action initiatives – farmer groups)

4) Location variables (***L***): District of survey: Kirinyaga, Bungoma and Migori districts

The implicit functional form estimated to assess the drivers of the decision to participate in markets is given by:

Participation = f (gender, log of age, occupation, distance to output market,, number of crop enterprises, household size, log of crop income , use of ICT, log of assets, area cultivated, education, years of farming experience, group membership, district dummies) + e (4)

2.1.2 Drivers of intensity of participation in collective action initiatives

The intensity of participation in collective action in this study refers to the number of years of actively participating in a collective action initiative (farmer group) from the day of enrolling/enlisting. Anytime period greater than 6 months was considered a year since most cropping seasons happens within this period. The number of years of participation farmer assumes integer values of discrete nature and is therefore a nonnegative count variable. Count data are non-normal and hence are not well estimated by Ordinary Least Squares (OLS) regression (Maddala, 2001).

The most common regression models used to analyze count data models include the Poisson Regression Model (PRM), the Negative Binomial Regression Model (NBRM), the Zero Inflated Poisson (ZIP) and the Zero Inflated Negative Binomial (ZINB). The PRM and NBRM regression models have become the standard models for the analysis of response variables with nonnegative integer (Winkelmann and Zimmermann, 1995; Greene, 2008; Kirui, Okello & Nyikal, 2010). The last two (ZIP and ZINB) are specifically used to account for cases with frequent zero counts (i.e. when there are more zeros than would be expected), which is not the case in this study. Only the PRM is therefore discussed here since the response variables were nonnegative integers and with only a few zero counts. In addition, test of overdispersion and underdispersion, common problems that render estimates of PRM biased and inefficient and justify the use of NBRM, found absence of these problems in the estimated PRM.

Greene (2008) argues that PRM models (for analyzing count data) are much closer to OLS regression model than other discrete choice models. This is because, just like OLS, the optimality conditions can be derived from the PRM models and that violation of variance assumptions in the models does not necessarily result in inconsistent estimators but rather the coefficient estimates are inefficient and standard errors are potentially biased (Wooldridge, 2002). Poisson regression model is therefore normally the first step for most count data analyses

(Areal, et al., 2008). Its density function of PRM is given by (Greene, 2003 & 2008; Wooldridge, 2002):

$$f(y_i|x_i) = \frac{e^{-\lambda(x)}\lambda_i(x)^y}{\Gamma(1+y_i)} \tag{5}$$

Where

$\lambda_i = \exp(\alpha + X'\beta)$ and $y_i = 0,1,\ldots,i$ is the number/count of services used (in our case); X = a vector of predictor variables.

Wooldridge (2002) and Greene (2003; 2008) show that the expected number of the events, y_i (i.e., number of calls made) per period is given as:

$$E(y_i|x_i) = \mathrm{var}[y_i|x_i] = \lambda_i = \exp(\alpha + X'\beta) \quad \textit{for } i = 1, 2, \ldots, n. \tag{6}$$

The log-linear conditional mean function $E(y_i|x_i) = \lambda_i$ and its equi-dispersion $Var(y_i|x_i) = \lambda_i$ assumptions constitute the main features of Poisson regression model (Greene, 2008). The log-linear regression models accounts for the nonnegative restriction imposed by Poisson on the dependent variable (Winkelmann and Zimmermann, 1995). Based on Equation (6), we specify the implicit functional form of the model estimated to examine the intensity of participation in collective action initiatives as;

Years of participation = Participation = f (gender, log of age, occupation, distance to output market,, number of crop enterprises, household size, log of crop income , use of ICT, log of assets, area cultivated, education, years of farming experience, group membership, district dummies) + e (7)

2.2. Study area, sampling procedure and data

This study was part of a wider project implemented by Electronic Agricultural Research Network in Africa (eARN-Africa). The aim of the project was to evaluate the effectiveness of ICTs in helping smallholder farmers commercialize and was implemented in three different districts each in a separate province. These include Kirinyaga (Central province), Bungoma (western province) and Migori (Nyanza province). These districts were characterized by poor access to markets by small farmers and reliance on agriculture. The study districts were selected to represent diverse agro-ecological zones, socio-economic environment, cultural diversity and varying production systems. For example, Kirinyaga district is considered a high potential area with export oriented export crops (French beans, baby-corn and Asian vegetables). Bungoma district on the other hand grew mainly maize with sugarcane while Migori is considered low potential area with main crops grown being maize and tobacco. Thus the choice of the districts presents differing levels of commercialization. Kirinyaga district is mainly inhabited by people of Kikuyu ethnic group while Bungoma and Migori districts are mainly inhabited by Luhya and Luo ethnic groups respectively.

Sampling procedure was done in three stages. First, the three districts (project districts) were purposely selected. Second, in each of the district, a location was randomly identified. A list of all farm households was then drawn with the help of local administration (village elders and area agricultural extension officers). Third, the respondents were then randomly sampled from the lists. A total of 379 farmers were interviewed in this study. The data collected included household characteristics, socio-economic indicators, household assets, information sources, ownership and use of mobile phones, sources and uses of income, among others. The household survey was conducted during March and April of 2010.

3. Results

3.1 Descriptive analyses of selected household variables and characteristics

The results of the descriptive analyses showing the test of mean difference between participants of collective action initiatives verses non-participants are presented Table 1. The study compares a total of 379 farmers; comprising of 234 participants and 145 non-participants. The t-values suggest that there were differences between participants and non-participants with respect to farmer-specific, farm-level and asset endowment characteristics. Specifically, among the farmer/household specific variable, there appears to be differences in age of the household head and the size of household. Participating households had significantly older heads (45 years) compared to the non-participating households (41 years). Similarly, participating households had significantly higher household size (6 persons) as compared to their counterparts (5 persons). Among the farm level characteristics, distance to local market and number of crop enterprises (proxy for risks) were significantly different between the two groups. The average distance to the nearest local market was about 2.5 km away for participating households compared to 1.5km for non-participating households while the number of crop enterprises was 3.2 and 2.4 for participating and non-participating households respectively.

Asset endowment characteristics show that participants in collective action possessed more land (6.8 acres) as compared to non-participating ones (5.4 acres). Similarly, natural log of income from farming activities as well as natural log of total income was higher (8.6 and 11.08) for participating households as compared to the non-participants (6.7 and 10.7) respectively.

Table 1: Summary statistics of selected household variables and characteristics

Variable Name	Variable Definition	Members (n=234)		Non-members (n=145)		Mean Differences	
		Mean	Std. Dev.	Mean	Std. Dev.	Diff.	p-value
Farmer/household specific variables							
Age	Age of household head (years)	45.15	13.57	40.86	13.99	4.28***	0.003
Male	1 if gender of household head is male, 0 otherwise	48.6%	0.50	52.4%	0.50		
Occupation	1 if main occupation is farming, 0 otherwise	91.2%	0.29	87.6%	0.34		
HH size	Size of the household (number of household members)	6.01	2.25	5.32	1.95	0.68***	0.003
Adult equivalent	Adult equivalent of the household members	3.03	0.94	2.66	0.79	0.37***	0.000
Farm-specific variables							
Local market dist.	Distance to the nearest local market center (km)	2.51	1.84	2.06	1.55	0.45**	0.014
Output market dist.	Distance to the nearest agricultural output market (km)	5.58	5.28	5.16	4.48	0.42	0.425
Bank dist.	Distance to the nearest commercial bank (km)	7.80	6.93	6.73	6.08	1.07	0.128
Extension agent dist.	Distance to agricultural extension field office (km)	9.99	6.01	9.34	6.55	0.65	0.324
Farm enterprises	Number of crop & livestock enterprises within the farm	3.21	1.61	2.43	1.21	0.78***	0.000
Capital endowment variables							
Education	Education level of household head (years of schooling)	8.53	3.64	8.17	3.69	0.36	0.347
Farming experience	Years of farming experience (years)	18.52	11.22	16.72	12.39	1.79	0.147
Land size	Total land owned by the household (acres)	6.81	7.53	5.40	5.98	1.41*	0.056
Ln farm income	Natural log of crop income	8.56	3.75	6.71	4.64	1.86***	0.000
Ln non-farm income	Natural log of other non-farm income	10.27	1.54	10.17	1.59	0.10	0.546
Ln total income	Natural log of total household income	11.08	1.28	10.71	1.46	0.37**	0.010
Ln assets	Natural log of assets	10.65	1.40	10.44	1.45	0.21	0.170
Regional dummy variables							
Kirinyaga	1 if farmer is located in Kirinyaga district, 0 otherwise	34%	0.48	32%	0.47		
Bungoma	1 if farmer is located in Bungoma district, 0 otherwise	40%	0.49	26%	0.44		
Migori	1 if farmer is located in Migori district, 0 otherwise	26%	0.44	42%	0.50		

Source: Author's compilation. Note: *, ** and *** denote significance of mean difference at the 10%, 5%, and 1% level, respectively.

3.2 Determinants of participation in collective action initiatives

The results of the Logit regression model estimated to assess the determinants of participation in collective action initiatives along with the marginal effects are presented in Table 2. As shown, a number of factors condition participation in collective action initiatives. Notably, among the farmer-specific characteristics, age, gender and household size are significant in influencing the decision to participate in collective action initiatives. A unit increase in the natural log of age decreases the likelihood of a farmer participating in collective action initiatives by 0.359, holding other factors constant while a unit increase in household size increases the likelihood of a farmer participating in collective action initiatives by 0.032. Female household heads were more likely to participation in collective action initiatives than their male counterparts by 0.146 ceteris paribus probably because such farmers engage a lot with other women and will need to seek input and output information from multiple sources using multiple strategies including fellow female farmers in the social groups.

Table 2: The propensity score for participation in collective action initiatives

	Logit Estimates			Marginal Effects		
Variable	Coef.	SE^b	p-value	Coef.	SE^b	p-value
Household specific variables						
Ln age	1.644**	0.648	0.011	0.359**	0.151	0.018
Gender (female)	0.685***	0.259	0.008	0.146**	0.059	0.014
Occupation	-0.032	0.403	0.936	-0.020	0.093	0.826
HH size	0.121*	0.070	0.087	0.032**	0.017	0.049
Farm-specific variables						
Output market dist.	0.013	0.024	0.588	0.002	0.006	0.706
Extension agent dist.	0.065*	0.026	0.098	0.015	0.006	0.103
Bank dist.	-0.067**	0.030	0.023	-0.015**	0.007	0.023
Number of crops	0.352***	0.098	0.000	0.085***	0.023	0.000
Capital endowment variables						
Education	0.018**	0.038	0.040	0.011**	0.009	0.047
Farming experience	-0.021	0.017	0.205	-0.005	0.004	0.239
Land size	0.015	0.019	0.426	0.005	0.005	0.270
Ln non-farm income	-0.285**	0.137	0.037	-0.065**	0.032	0.041
Ln total income	0.378**	0.169	0.025	0.091**	0.039	0.022
Ln assets	0.039	0.091	0.667	0.009	0.021	0.667
Input per capita	0.000	0.000	0.552	0.000	0.000	0.571
Regional dummy variables#						
Kirinyaga	0.462	0.325	0.155	0.108	0.072	0.131
Bungoma	0.709**	0.320	0.026	0.228***	0.070	0.001
Constant	-8.829***	2.438	0.000			

Number of obs. = 379 Pseudo R2 = 0.4719 Prob > chi^2 = 0.0000
LR chi^2(17) = 136.75 Log likelihood = -882.57

Source: Author's compilation. *b*: Standard errors (SE) are robust.
Notes: $^{*, **, ***}$ denote significance at the 10%, 5%, and 1% levels, respectively.
The dependent variable is a dummy (*1= participation in collective action group, 0 =otherwise*)

Among the farm specific variables, nearness to extensions market, distance to bank and the number of crop enterprises grown by the farmer are significant in influencing the decision to participate in collective action initiatives. Specifically, a unit increase in the distance to the nearest agricultural extension office increases likelihood of participation in collective action initiatives by 0.015 ceteris paribus. A unit increase in number of crops output market increases likelihood of using ICT tools by 0.085 suggesting that ICT tools are an important option for cutting down on transaction costs incurred in obtaining market information. This finding suggests that farmers who are risk averse are more likely to participate in collective action initiatives so as to seek opinion from fellow farmers. Participation in collective action initiatives alley fears experienced by farmers in adopting technologies and trying new farming practices.

Results further show that, among capital endowment variables, education level, non-farm as well as total farm income positively influence the decision to participate in collective action initiatives. Holding other things constant, a unit increase in education and natural log in total household income increase the likelihood of participate in collective action initiatives by 0.011 and 0.091, respectively. However increased in log of non-farm income by 1 unit degreases level of participation in collective action by 0.065. This result that endowment with physical assets reduces the likelihood of using participation in collective action is rather unexpected but may suggest that farmers that are more asset-endowed are more able to access markets and are already participating as compared to their counterparts. Among the location variables, the coefficient of one of the dummies representing the districts the study was conducted in is positively statistically significant. Specifically, the results show that moving from Bungoma to Migori increases the likelihood of participating in collective action initiatives. This finding is in line with our apriori expectations. Farmers in Bungoma produce market-oriented crops hence are more likely to participate in the market exchanges.

3.3 Drivers of intensity of participation in collective action groups

The results of the Poisson Regression Model (PRM) estimated to assess the determinants of intensity of participation in collective action initiatives along with the marginal effects are presented in Table 3. As shown, similar to decision to participate in collective action initiatives, a number of factors condition intensity of participation in collective action initiatives. Notably, among the farmer-specific characteristics, age, gender, main occupation and household size are significant in influencing the decision to participate in collective action initiatives. A unit increase in the natural log of age decreases the intensity of a farmer participating in collective action initiatives by 0.162, holding other factors constant. A unit increase in household size increased the extent participation in collective action initiatives by 0.087. Being female increased the extent of participation in collective action initiatives by 0.369, ceteris paribus. practice farming as a primary occupation increased the extent of participation in collective action initiatives by 0.302. This may be the case because farmers who engage in farming full time are more likely to produce more and hence will need to engage more in input and output markets more often.

Table 3: Drivers of intensity of participation in collective action initiatives

	Poisson Estimates			Marginal Effects		
Variable	Coef.	SE^b	p-value	Coef.	SE^b	p-value
Household specific variables						
Ln age	0.330*	0.198	0.095	0.162*	0.396	0.094
Gender (female)	0.332***	0.077	0.000	0.369***	0.156	0.000
Occupation	0.264**	0.122	0.031	0.589**	0.302	0.041
HH size	0.044**	0.021	0.038	0.087**	0.042	0.038
Farm-specific variables						
Output market dist.	-0.001	0.008	0.895	-0.002	0.017	0.895
Extension agent dist.	0.063***	0.024	0.008	0.126***	0.047	0.007
Bank dist.	-0.019	0.009	0.236	-0.038	0.018	0.235
Number of crops	0.015**	0.006	0.021	0.030**	0.013	0.021
Capital endowment variables						
Education	0.023*	0.012	0.057	0.045**	0.024	0.056
Farming experience	0.003	0.005	0.528	0.006	0.010	0.528
Land size	-0.013*	0.007	0.067	-0.027*	0.015	0.066
Ln non-farm income	-0.038	0.036	0.302	-0.075	0.073	0.302
Ln total income	0.147***	0.047	0.002	0.294***	0.093	0.002
Ln assets	-0.014	0.028	0.617	-0.028	0.056	0.617
Input per capita	0.020	0.004	0.870	0.000	0.000	0.870
Regional dummy variables#						
Kirinyaga	0.681***	0.110	0.000	0.557	0.282	0.204
Bungoma	0.602***	0.115	0.000	0.346***	0.284	0.000
Constant	-2.151***	0.764	0.005			
Number of obs. = 379	Pseudo R2 = 0.4111		Prob > chi^2 = 0.0000			
LR $chi^2(17)$ = 7 1.71	Log likelihood = -216.57					

Source: Author's compilation.
The dependent variable is a count variable (number of years actively participated in CA group)
Notes: *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.
#: District dummies included in estimation to control for district fixed effects
b: Standard errors (SE) are robust.

Among the farm specific variables, nearness to extensions market and the number of crop enterprises grown by the farmer are significant in influencing the extent of participation in collective action initiatives. Specifically, a unit increase in the distance to the nearest agricultural extension office increases likelihood of participation in collective action initiatives by 0.126 ceteris paribus. When farmer cannot obtain help from fellow farmers when the official extension officers are far. A unit increase in number of crops output market increases the extent of using participation in collective action initiatives by 0.030. This further strengthens the suggestion that collective action plays a big role absolving fears farmers face. Results further show that capital endowment variables such as education level, land size and total income are significant drivers of extent of participation in collective action initiatives. Holding other things constant, a unit increase in education and natural log in total household income increase the likelihood of participate in collective action initiatives by 0.045 and 0.294, respectively. Increased income contributed from farming activities may trigger further collaborations among farmers and hence facilitate social capital accumulation. However, an increase in natural log of land size by 1 unit decreases extent of participation in collective action by 0.027 holding other factors constant. This may be explained by the fact that large piece of land may call for different operations such as mechanization and with limited similarities with the local communities. Other factors constant, results show that moving district dummy for Bungoma (moving from Migori to Bungoma) increases the extent of participating in collective action initiatives by 0.346.

3.4 Effect of participation in collective action initiatives on market participation and incomes

In order to estimate the effect of participation in collective action initiatives, we test the difference in mean of commercialization and incomes between group participants and non-participants. Results are presented in Table 4. There exist significant differences in mean output and input market commercialization of 12% and 6% respectively. There also exist a significant difference in mean incomes obtained by participants and non-participants. Participants receive higher crop income by about Ksh. 5,613 and higher crop and livestock income by Ksh. 5,342.

Table 4: Effect of participation in collective action initiatives on market participation and incomes

	Participants (n=234)		**Non -participants (n=145)**		**Differences**	
Variable	Mean	Std. Dev.	Mean	Std. Dev.	Mean Diff.	p-value
Output market commercialization	0.58	0.31	0.46	0.36	0.12**	0.021
Input market commercialization	0.19	0.18	0.13	0.18	0.06***	0.001
Crop income	20941.94	17375.74	15328.68	26554.87	5613.26**	0.014
Crop and Livestock income	43825.98	23084.22	38483.62	20,224.04	5342.36*	0.079

Source: Author’s compilation.

Notes: *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

4. Conclusions and Recommendations

This study assessed the determinants of participation and intensity of participation in collective action initiatives. It also examined the effect of participation in such initiatives on household commercialization and on household welfare (incomes). It uses a double hurdle approach (a Logit regression model to examine the determinants of participation in collective action and a Poisson regression model to assess the factors that determine the intensity of participation). The study then tests the difference in means incomes and commercialization between participants and non-participants.

Results show that farmer/household specific variables (age and household size), farm specific variables (distance to agricultural extension agent, distance to the nearest commercial bank and number of crop enterprises), capital endowment variables (income and education) and regional dummy variable (district of survey) influence the decision to participate in collective action initiatives. Similarly farmer/household specific variables, farm specific variables, endowment variables and regional dummy variable also influence the extent of participate in collective action initiatives. Results also indicate that there exist significant differences in output and input market participation (commercialization) and in mean incomes as a result of participation in collective action initiatives. The implication of these findings is that for collective action initiatives to be to be effective in achieve the desired goals of helping farmers commercialize, capacity of farmers (e.g. through trainings) to operate and manage them should be improved. Stronger linkages with other institutions like public institutions, credit institutions should be encouraged and fostered so as to address the needs of the farmers.

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