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Influence of Collective Action Participation on Technical Efficiency among Smallholder Producers: A Case of Banana Farmers in Kisii and Nyamira, Kenya

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Abstract The main aim of the paper is to analyse the influence of collective action participation defined as group participation on technical efficiency among smallholder banana producers in Kisii and Nyamira Counties, Kenya. Using stochastic frontier approach, the study evaluated how farmers in collective action differ from non-collective action participants in terms of technical efficiency levels of banana production as well as the factors responsible for inefficiencies among farmers. Logistic regression model is also used to determine the characteristics of group participation among the smallholder producers. The findings were based on cross-sectional data with a sample size of 260 smallholder banana producing households obtained through a multi-stage sampling technique. From the results obtained from logistic regression, salaried occupation had a significant adverse effect on group participation, while age, gender, education level, informal occupation, mobile phone ownership and access to extension advice had a significant positive impact. Besides, the stochastic production frontier model estimates showed that group members were more technically efficient than non-members at the 1% significance level. Field size, use of manure and inorganic fertilizer had a significant positive effect on productivity levels with high returns to scale exhibited among non-group members. Inefficiency levels were significantly affected by the age, gender and occupation of the household head. In conclusion, collective action helps farmers to address various production needs, thus making them more technically efficient.

Keywords: *stochastic frontier model, group participation, inefficiency levels*

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1. Introduction

Banana (*Musa spp.*) is an important food crop valued as world's fourth valuable crop with high nutritive and health benefits [1]. The crop provides 25% carbohydrates, 10% calories, and vitamin A, B6, C and D. In addition, it is a source of essential minerals such as potassium and magnesium which are vital in maintaining healthy circulatory and digestive systems respectively [1]. Due to the health and nutritional benefits, banana per capita consumption has been increasing across sub-Saharan Africa [2]. In Kenya, ripe banana is one of the highest consumed fruits among the urban residents, while the plantains are ranked second across all income groups [3]. Apart from its contribution to food security, the crop is also a source of income to the economy with high profitability potential. Increasing banana productivity levels would therefore contribute to a healthy and food secure society, and impact positively on rural development [3,4].

There have been various interventions to increase the productivity levels of banana to meet the excess demand, but the production levels still remain below optimum [5]. For instance, the Kenya Agricultural and Livestock Research Organization (KALRO) has continuously come up with new agronomic practices, and improved banana varieties which are disease resistant, high yielding and mature faster than the traditional varieties [6]. Unfortunately, majority of farmers still use traditional farming methods and indigenous crop varieties. These varieties take longer time to mature, highly prone to disease attack, and require more space to grow with uneven yields. However, the high yielding varieties require more fertilizers; intensive labour and specific skills for its successful propagation and optimum yields. The additional costs lock out majority of smallholder farmers from adopting new technologies. These smallholders also suffer from credit constraints, low asset endowment and lack of infrastructure [7]. Information asymmetry has made it more difficult for the smallholder producers to access production related information on research findings.

Majority of farmers in Kisii and Nyamira counties rely on banana production as a major economic activity with the crop ranked as most important cash crop together with tea in the two counties [8]. Banana production earns the region an average of 10.25 million USD annually [2]. At farm level, a farmer can earn 1500 USD per hectare per year on average from sales of fresh banana. Like other smallholder farmers, majority of the farmers in this area are faced with challenges of limited resource endowment. Land in these counties is highly fragmented such that most farmers access land holding ranging from 0.2 to 2.1 acres. This is largely due to high population density which has put much pressure on agricultural land [9]. The farmers are also faced with budgetary constraints which limit them from affording important agricultural inputs to enhance productivity. Recognising the challenges of limited input access and budgetary constraints, productivity levels can only be increased in farmers becoming more technically efficient.

To cope with the above challenges, there are those farmers in the region who have joined collective action through intervention by different stakeholders. This is done to gain mutual support through enhanced farmer coordination which reduces information asymmetry; and better manage transactions thereby reducing associated costs [10]. For example, since the year 2003 Africa Harvest (AH) has worked with existing farmer groups in the area to enhance farmer technical capacity so as to increase productivity and income from banana enterprise. The organization also helped to link the producers to extension service providers, increase their access to Tissue Culture (TC) seed types through greenhouse technology and nursery establishment [11]. This paper is going to provide information on farmer characteristics which influence collective action participation, and levels of Technical Efficiency between group participants and non-participant banana producers in Kisii and Nyamira Counties.

In Africa, banana is mainly produced in Eastern and West Africa. West Africa produces 32% of worldwide plantain total production; Eastern Africa is the highest producer of highland bananas in Africa and contributes 20% to the worldwide banana output [2]. Uganda is the second largest banana producer worldwide after India, with an estimate of 10.6 million metric tonnes annually. There are four main types of bananas grown in Eastern African region; the cooking type referred to as *matooke* in Uganda, beer bananas mainly in Burundi and Rwanda; and the dessert and juice types [5].

Banana production in Kenya is mainly practised in the Central, Eastern and Western regions. The crop is produced in regions of altitude between 0 to 1800 metres above sea level. In Kenya banana occupies approximately 2% of total arable land which translates to about 80,000 ha. Statistics show that the total physical production stands at approximately 1 million tonnes annually translating to an average productivity of 12.5 tonnes/ha of bananas against a potential of 40 tonnes/ha/year [12]. This contributes to 50% of the total domestic horticultural production in Kenya [8]. In Kisii and Nyamira, the commonly produced are the green banana commonly referred to as the cooking variety while the desserts are commonly grown in the eastern and central Kenya [4]. The total annual production of banana in the two counties is averagely 7000 metric tonnes according to horticultural department in 2017.

Table 1. Summary of green and ripe banana varieties

Green (cooked) type	Ripe (dessert) type
Uganda green	Apple banana (*Sukarindizi*)
Kiganda	Chinese Cavedish
Nusung'ombe	Dwarf Cavedish
Ngombe	Giant Cavedish
Mutahato	*Bokoboko*
Gradishikamane	*Muraru*
	Kampala
	Bogoya
	Gros Michel

Source: Ministry of Agriculture (2017).

An upward trend with regard to area under banana production has been witnessed in the past three decades. However, there is no proper correlation between this trend and the resultant yields. Despite the increase in acreage under banana production, output has remained very low and stagnated within a range of 4-15 tonnes/ha against a potential of 30-40 tonnes/ha [13]. In this paper we will provide recommendations on ways to increase productivity levels.

Collective action participation is typically framed to resulting in some shared results, outcome, or public good which are non-excludable for relevant entities regardless of the contributions they have towards its realization [14]. Performance of collective action can be analysed in relation to natural resources and more significantly to public good and collective good where some scholars have identified certain factors to consider. The factors fall under four categories which include resource system characteristics; group characteristics; Institutional arrangements; and the external environment [14]. In this paper, it is assumed that those who participate in collective action enjoy those attributes which influence performance of collective action.

Farmers' participation collective action is mostly influenced by socio-economic, technical and physical factors according to empirical studies. Some of the socio-economic factors which have been found to influence collective action participation are age, gender, type of occupation, household size, marital status, education level, property rights and income levels. For instance, in study by [15], gender was found to be a significant factor. Households where the female had a role in decision making were more likely to join such organizations [15]. According to [13], land size, asset ownership, credit access positively and significantly affected group participation. In the study, age of the farmer, size of land holding, credit accessibility and market proximity had significant and positive impact on probability of membership.

Using logit model, [16] found that marital status, distance to group meeting point as well as age of the farmers had significant impact on group participation. That study showed a positive correlation between age and group participation. Married farmers also showed high likelihood of joining groups compared to the unmarried lot. The results from the study however, showed that as the distance to the source of information increases, the chances of group participation also increases [16]. The

latter finding contradicts other literatures which have shown farmers reluctance to join groups when the convening point is far away [13]. The literature shows that farmers consider both endogenous and exogenous factors when making decision to join groups. However, there are some contradictions on how different farmers decide faced with similar socio-economic or physical characteristics. This calls for further research in the area to give more consistent information.

A look at further literature also reveals various socioeconomic, physical and technical factors that influence farmer technical efficiency [16]. The most commonly used methodology by majority of researchers in determining the level of technical efficiency is the Stochastic Frontier Approach (SFA) and the non-parametric Data Envelopment Analysis (DEA). For instance, [17] used SFA in estimating the technical efficiency levels of oil palm production in Indonesia. In the study, [17] found that gender of the farmer had a significant effect on technical efficiency; male farmers were less technically inefficient than the female counterparts. In Ogun state of Nigeria, a study by [18] to estimate the technical efficiency of maize production using SFA approach showed household size and educational levels as major determinants of technical inefficiency of farmers. In the study, it was found that increase in household size reduced inefficiency of production which could be attributed to labour availability. However, higher education levels increased inefficiency, a finding which contradicts findings from other studies [18]. For instance, in a study to determine maize and fruit farmer technical efficiency in Cameroon, education level was found to positively influence technical efficiency levels in maize and fruit production systems [19]. While determining productivity and technical efficiency of cocoa production in eastern Ghana, farmer experience, gender and number of extension visits were found to have significant impact on technical efficiency [20]. In the study, male farmers were found to be less technically inefficient than the female counterparts. The literature above reveals similarity between factors affecting collective action participation and those that affect technical efficiency of farmers. In this paper we provide more information on this relationship.

2. Materials and Methods

2.1. Sampling and Data Collection

The sample for the study was obtained from a two-stage stratified cluster sampling where the first stage involved selection of rural clusters from Kisii and Nyamira Counties from the Kenya National Bureau of Statistics (KNBS) household-based sampling frame through National Sampling Survey Evaluation Program V (NASSEP V). The process was done using Equal Probability Selection Method (EPSEM). The second stage randomly selected a uniform sample of 20 households in each cluster from a roster of households in the cluster using systematic random sampling method. The sample size was calculated to provide representative estimates for the main domain of interest: the six Agro Ecological Zones (AEZs). These were: Upper Highlands (UH), Lower Highlands Upper Midlands (UM) - two zones, and Lower Midlands (LM) - two zones. The allocation of the sample to the AEZs was done using the square root allocation method to ensure that the smaller AEZs got adequate sample. It was distributed in the rural strata across the counties. In each AEZ, systematic random sampling procedure was used to obtain the required sample. During data collection, there was no allowance for replacement of non-responding households.

A sample size of 260 smallholder banana producer households across the two counties was obtained from the process whereby 160 households interviewed were members of collective action which is about 60% of the sample. Non-group participants comprised the remaining 40%. The survey was implemented between July and September, 2014 and contains data for the 2013/2014 cropping year.

2.2. Data Analysis

2.2.1. The logistic Regression Model

In this paper we used this model to determine the factors that influence farmer's participation in collective action. Logit model enables the handling of both ordinal and nominal data independent variables; more so there was assumption that the model has a nonlinear relationship between the dependent and independent variables. Moreover, group membership is endogenous, thus could be affected by self-selection problem, however the problem of selection bias does not affect logit regression. The study is based on the assumption that group membership depends on associated potential costs and benefits depending on the perception by different households. Costs such as opportunity of time and group membership fees could be some of the negative incentives whilst better access to input markets, technology and information could provide positive incentive for group participation.

Farmers in the area are also assumed to be rational in decision making and would only join collective action if the benefits would be higher than the costs. Consequently, decision by a household to participate in a collective action was modelled in a random utility framework which has been commonly applied to evaluate adoption of innovations under uncertainty [21,22]. In this study the decision is modelled as a binary choice with assumption of utility maximization by the banana producer, subject to resource constraints [23]. A farmer would therefore choose to join a group if the utility, U_c derived from group participation is higher than utility derived from non-participation, U_i. The utility, U_i of a farmer in the study is expressed as a function of various household exogenous variables, X_i and a vector parameter β.

$$U_i = V_i(\beta X_i) + u_i \quad (1)$$

Where: u_i is the error term. Important to note is that group participation decision is affected by both external and internal household factors. From previous literature the internal factors that were expected to influence farmer decisions were mainly farmer characteristics such as age, gender, education, household size and marital status among others. The external factors were expected to be

access to extension, farm resources, among others [24]. The probability of a banana producer being group participant was therefore given by $P(u_i < \beta X_i)$. The probability of group participation was then estimated as:

$$P(C=1) = P(u_i < \beta X_i) = V_i(\beta X_i) + u_i \quad (2)$$

Where: P denotes probability, C = 1 for group participant, C = 0 for non-participant. The model was generally expressed as:

$$P(1,0) = \beta_0 + \beta_1 X_1 + ... + \beta_n X_n + \mu,\ \mu \sim N(0,1). \quad (3)$$

Where, X denotes various farmer household characteristics, and infrastructural factors

2.2.2. Stochastic Production Frontier

The efficiency of a firm is defined as its actual productivity relative to maximal potential productivity [26]. Measurement of technical efficiency is typically done by either parametric or non-parametric techniques. Parametric methods include production, cost, profit and revenue functions as alternative methods of describing the production technology and efficiency level determination which specifically involves estimation of the stochastic frontier. The Stochastic Frontier Approach (SFA) allows the estimation of maximum attainable output for a given set of inputs. It also allows incorporation of other factors beyond input and prices in the model, thus reveals all factors that influence the producer's ability to become efficient [25]. The parametric approach explicitly recognizes that production function represents a technically maximum feasible output level for a given level of farm inputs.

In a non-parametric model, for example Data Envelopment Approach (DEA), the structure of the model is not specified *apriori*, but is determined from the available data. The strengths of non-parametric technique are that it does not require assumptions on the distribution of the error terms of the frontier production function hence it does not impose a specific structure on the technology. The technique allows use of disaggregated data and does not suffer from heteroscedasticity and multicollinearity. However, the approach is highly susceptible to outliers and inconsistencies in the data [27]. In this study, SFA was used to determine the scores of technical efficiency as well as factors that affect technical inefficiency of a banana farmer. The function was derived from a Dobb-Douglas self-dual estimation function specified as;

$$Y = f(x,\beta)e^{(v-\mu)} \quad (4)$$

Where Y is the output, $f(x,\beta)$ denotes the frontier production function and $v-\mu$ is the error term, v_i is a random variable assumed to have normal distribution N(0, σ^2v) and independent of μ_i which is a non-negative random variable assumed to account for technical inefficiency. The two stage estimation procedure stems from literature by [27] who reported that individual farm-specific characteristics which technical efficiency of decision making units are not included in the conventional specification of the production function since they are not direct production units. The two-stage estimation will therefore allow incorporation of socio-economic characteristics since they have a roundabout effect on production. Generally Technical Efficiency function is specified as;

$$TE_i = \sum X_{it}P_i / \sum X_i P_i. \quad (5)$$

The function is however highly restrictive with respect to returns to scale and elasticity. Therefore, unrestricted trans-log model of Maximum Likelihood Estimation (MLE) was used to estimate the overall level of Technical Efficiency. The general form of model was specified as;

$$\ln Y = \beta_0 + \sum_{i=1}^{n}\beta_i \ln X_i + \sum_{i=1}^{n}\beta_i Z_i + \sum_{i=1}^{n}\sum_{i=1}^{n}\beta_i (\ln X_i)^2 + \sum_{i=1}^{n}\sum_{i=1}^{n}\beta_i (\ln Z_i)^2 + \sum_{i=1}^{n}\sum_{i=1}^{n}\beta_i \ln X_i \ln Z_i + \beta_k D_k + (v-u) \quad (6)$$

Where: ln denotes natural logarithm, Z are conditioning factors, D is dummy variable representing farmer and farm characteristics. The Elasticity of production of a given farmer i using j inputs was determined by the equation below:

$$E_{ji} = \beta_j + \beta_{ji} \ln X_{1i} + \beta_{j2} \ln X_{2i} + ... + \beta_{jn} \ln X_{ni}. \quad (7)$$

To determine the factors which influence level of technical inefficiency, the second stage of MLE which incorporates household exogenous variables in the model was specified as:

$$\mu = \alpha_0 + \alpha_1 x_1 + ... + \alpha_n x_n + \varepsilon \quad (8)$$

Where: μ denotes technical inefficiency scores, x denoted the household covariates, other farmer characteristics and group factors.

3. Results

3.1. Descriptive Statistics

Table 2 shows summary statistics for means and standard deviations of various socioeconomic characteristics of the overall sample size used in the survey, as well as comparison between group-members and non-group members. From the results, the overall house-hold size had a mean of 6.3 and a standard deviation of 3.460. The small standard deviation shows that most of the households had a size of 3 to 9 members. Comparison of household size between group members and non-members in the same Table 2, there was a relatively higher average household size for collective action participants (6.72) compared to 5.64 for non-participants. The average age of all the participants in the survey was 47.154 years old with a standard deviation of 12.522. It means that, the majority of the farmers interviewed were aged between 34 and 50 years old. The mean age of farmers in collective action members was found to be relatively higher than that of non-collective action members. The non-group members reported a mean age of 41.34 with a standard deviation of 12.958, which means the majority of this farmer category were between 28 and 53 years old. The mean age of

collective action participants was reported as 50.788 with a standard deviation of 10.785. That means the majority of group members interviewed were between 40 to 60 years old.

Table 2 also reveals that, the overall mean of the gender of the respondents was 0.554 which means the sample size was non-bias against any gender. However, in the same Table, it could be seen that non-group participants registered a higher mean of 0.638 compared to group participants who registered a mean of 0.420. Gender was a binary variable coded as 0 for the male and 1 for the female. The difference in means show that the majority of non-group members were male whereas the majority of group members were female. The marital status of the farmers shows a mean of 0.915 which means the majority of the respondents reported to have married. On marital status both non-group members and group members reported higher means of 0.860 and 0.950 respectively. That indicates there was a higher number of farmers who said they have never married among the non-group members as compared to group members. Marital status was coded as a binary variable with zero (0) for farmers who have never married (single) and one (1) for married farmers, therefore the more the mean is closer to 1 the higher the number of married individuals in the sample.

The highest completed education level of the banana farmer reveals that the overall mean education level attained was 10.595 which is equivalent to Form 2 in the Kenyan education system. The standard deviation was 3.921, that means the majority of the farmers had completed between standard 8 (primary school level) and form 4 (O' level). A comparison between group-members and non-members show a relatively higher mean education level (10.9) for group-members compared to non-group members (10.11). The table also shows that the majority of respondents own mobile phone, but radio. The overall mean of radio ownership (a binary variable) was reported as 0.438, while that of mobile phone ownership was 0.827. It means that higher proportion of respondents said no to radio ownership, whilst a higher proportion said yes to mobile phone ownership. By categorization, non-group members registered a higher mean (0.540) on radio ownership, whereas the group participants had a higher mean (0.956) on mobile phone ownership.

The total asset value reported an overall average mean of KES 24699.500 with a standard deviation of 73982.90. Group members recorded relatively higher mean asset value at KES 26349.500 compared to non-group members at KES 22208.00. Similarly, the average off-farm income was relatively higher among the group-members at KES 8672.018 compared to non-group members at KES.8238.500. The overall mean income was reported as KES 6838.846 and a standard deviation of 10367.870. It means the majority of the farmers earned between KES 5,000 and KES 17,000 from off-farm activities. In terms of occupation, farmers who engage in informal jobs were found to be more likely to join groups. The results revealed that the majority of group participants were found to engage in business and other forms of informal income activities with a mean of 0.306 compared to 0.06 of non-group members. In general, the majority of the farmers engaged in informal occupations posting a mean of 0.462 against 0.254 for salaried workers.

Table 2. Descriptive Statistics of Banana Producers by Collective Action Participation

	Non-group member (n=100)		Group member (n=160)		Total sample size (N=260)	
Variable	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std Dev.
Age of the farmer	41.340	12.958	50.788	10.785	47.154	12.522
Gender of the respondent	0.420	0.496	0.638	0.482	0.554	0.498
Gender of the head	0.221	0.423	0.415	0.496	0.338	0.475
Marital status of farmer	0.860	0.349	0.950	0.219	0.915	0.279
Education level of farmer	10.110	4.413	10.900	3.992	10.596	3.921
Size of the household	5.640	3.329	6.742	3.483	6.317	3.460
Radio ownership	0.540	0.501	0.375	0.486	0.438	0.497
Phone ownership	0.620	0.488	0.956	0.205	0.827	0.379
Total assets value (KES)	22208.000	55298.750	26349.500	83954.990	24699.500	73982.900
Off-farm income	8328.500	14531.170	8672.018	8444.710	6838.846	10367.870
Salaried occupation	0.330	0.473	0.069	0.254	0.169	0.376
Informal occupation	0.060	0.239	0.306	0.462	0.212	0.409
Distance to market (km)	4.333	6.746	3.983	3.011	4.118	4.795
Distance to motorable road	0.379	0.876	0.449	1.241	0.422	1.114
Credit received (KES)	6182.653	14583.400	28273.440	105906.500	19882.360	84468.170
Banana field size	0.38	0.35	0.43	0.40	0.41	0.38
Usage of fertilizer	0.28	0.45	0.52	0.50	0.43	0.50
Inorganic fertilizer (kg)	0.35	1.62	1.68	4.86	1.17	3.99
Organic manure used(kg)	53.44	126.72	158.79	254.56	118.27	220.35
Banana harvested(kg)	669.64	775.75	942.77	1262.71	837.72	1107.51

Source: Author Calculations from Tegemeo Institute Household Survey Data (2014).

Table 2 further shows, the overall mean distance to the nearest input market was 4.118km. The group participants reported a relatively lower mean distance as compared to non-members at 3.983km and 4.333km respectively. In terms of credit access, the results show that group-members reported higher mean of amount of credit receive in the last 12 months (KES.28273.40) compared to non-members at KES.6182.653. The average field size of banana in overall was 0.41 acres with a standard deviation of 0.38. The acreage means that the majority of farmers planted bananas in an area ranging from 0.03 acres to 0.79 acres. The group members had slightly higher mean acreage (0.40) compared to non-group members at 0.35 acres. Majority of farmers were not using fertilizer in banana production with a mean of 0.43. Group members posted a higher mean above the total average (0.52) relative to non-group members at 0.28. For those who used fertilizer, the majority applied organic at average of 118.27kg while inorganic was at 1.17kg. It was among the group participants where application of organic and inorganic fertilizers was higher with a mean of 158.79kg and 1.68kg respectively. Non-collective action participants posted lover mean from fertilizer quantities compared to their group counterparts, that was 53.44kg for organic and 0.35kg for inorganic fertilizer. The overall total quantity of banana harvested was 837.72kg on average. Group members had a higher mean of quantity harvested above the total average at 942.77kg compared to 669.64kg for non-group members.

Table 3 below gives a summary of categories of the producer groups by main activities of the groups. It also summarizes the position held by respondents in such groups. In the summaries, 61.88% of the group members belong to groups whose main activity were to provide agricultural inputs and credit services to members. Only 17.5% of the members belonged to groups that offer training as main activity. The rest of the farmers (20.63%) belonged to general welfare groups.

Table 3. Group Membership Proportion by Main Activity

		Proportion of members (%) n=160
Main activity of the group?	Training and capacity building	17.5
	Provision of inputs and credit service	61.88
	General welfare of banana farmers	20.63
Position in the group	Ordinary member	65.63
	Official in the group	34.38

Source: Author's calculations using Tegemeo Institute Household Survey Data (2014).

Table 4. Logit regression results on determinants of collective action participation

Group participation	Coefficient	Std. Err.	z	P>z	(dy/dx)
Household size	0.050	0.057	0.880	0.378	-0.011
Relationship to the head	-0.647	0.399	-1.429	0.105	0.135
Age of the farmer	0.055**	0.017	3.220	0.001	-0.012**
Gender of the farmer	1.338**	0.466	2.870	0.004	-0.282**
Are you married	1.066	0.763	1.40	0.163	-0.250
Highest level of education	0.138**	0.052	2.660	0.008	-0.029**
Main occupation formal(salaried)	-2.685***	0.547	4.910	0.000	0.586***
Main occupation informal	1.767**	0.654	2.700	0.007	-0.286**
Distance nearest market(Km)	-0.023	0.046	-0.510	0.608	0.005
Distance to motorable road (Km)	0.044	0.247	0.180	0.860	-0.009
Distance to tarmac road (Km)	-0.003	0.027	-0.130	0.900	0.001
Condition of nearest tarmac road	-0.151	0.219	-0.690	0.491	0.032
Radio ownership	-0.677	0.396	-1.710	0.087	0.143
Mobile phone ownership	2.204***	0.582	3.790	0.000	-0.500***
Receive extension services last 12 months	1.657***	0.431	3.840	0.000	-0.371***
Total asset value	0.000	0.000	1.440	0.149	0.000
Monthly off-farm income	0.000	0.000	-1.300	0.195	0.000
Amount of credit received	0.000	0.000	0.780	0.438	0.000
Field size (acres)	0.044	0.632	0.070	0.944	-0.009
Constant	6.676***	1.560			
LR chi2(19)	163.22				
Prob > chi2	0.000**				
Pseudo R2	0.471				
Number of observations	260				

Legend: * p<.05; ** p<.01; *** p<.001. (*) dy/dx is for discrete change of dummies from 0 to 1.
Source: Author's calculations using Tegemeo Institute Household Survey Data (2014).

3.2. Characteristics of Collective Action Participation by Smallholder Banana Producers

The factors were determined through a logistic regression model using various socioeconomic variables. As shown in Table 4, the variables used in the model were: age of the farmer, household size, off-farm income, level of education attained, gender of the farmer, household head, spouse, field size, salaried occupation, informal occupation, condition of the road, distance to the nearest market, phone and radio ownership, and total asset value of the household. The logit model showed a highly significant association between collective action participation and household socioeconomic characteristic (Prob.> chi2= 0.000). The marital status of the farmers was found to positively and significantly influence likelihood of collective action participation by a banana farmer. Married farmers were more likely to participate in groups. Moreover, the coefficient associated with marital status also shows that farmers in polygamous marriages are more likely to join groups. Gender of the farmer also had a highly significant association with group participation whereby female farmers were found to be strongly associated with collective action than their male counterparts. Significant effect was also recorded for the type of occupation and highest level of education attained by the farmer. There was positive association between education level of the farmer and likelihood of group participation with results showing 5% significance level. Salaried occupation had a statistically significant negative effect on group participation at 5% level. In terms of information access, the study found that mobile phone ownership had a positive and significant effect on likelihood of banana group participation at 1%. Distance to the market had positive significant impact on household decision on collective action participation at 5% level. Finally, access to extension advice increased probability of collective action participation by a household at 1% significant level.

3.3. Technical Efficiency Levels of Banana Production by Collective Action Participation

Estimation of the technical efficiency levels from the study was done using the stochastic frontier approach. The model allows the simultaneous estimation of factors which affect farm-level productivity as well as household covariates which are responsible for farm inefficiencies. The results were generated using a truncated form of maximum likelihood estimation. In the first stage of estimation, production inputs were incorporated in the model, which were: field size in acres, fertilizer in kilograms and quantity of organic manure used in kilograms. While executing the model, the interaction variable between fertilizer and manure for non-group members showed multi-collinearity and was dropped from the regression analysis. From the data obtained, it became apparent that 99% of sampled banana producers in the two counties used a local variety for the planting material, thus not included in the analysis due to lack of variability. The results of the truncated normal distribution showed gamma estimated at 0.092 and 0.022 for the group and non-group participants respectively. The results are as shown in Table 5.

Table 5. Stochastic Frontier Model Estimates by Group Participation

	Non-group participants		Group participants	
Variable	Coefficient	Std error	Coefficient	Std error
Constant	6.349***	0.364	7.624***	0.257
Log field size	1.382***	0.198	0.429***	0.199
Log quantity of fertilizer	1.185	0.724	0.357	0.103
Log quantity of manure	-0.338*	0.198	-0.016	0.188
Log field size squared	-0.099	0.063	0.226***	0.051
Log quantity of fertilizer squared	0.009	0.32610	0.121*	0.067
Log quantity of manure squared	0.097***	0.035	0.012	0.031
Log field-fertilizer interaction	-0.535***	0.163	0.175*	0.110
Log field-manure interaction	-0.053	0.039	-0.018	0.028
Log fertilizer-manure interaction	0.000	omitted	0.004	0.027
Sigma2	0.406	0.045	0.643***	0.079
gamma	0.0220		0.092	
Log-likelihood	-87.571		-187.008	
Number of observations	100		160	

Legend: * p<.05; ** p<.01; *** p<.001
Source: Author's Calculations Using Tegemeo Institute Household Survey Data (2014).

Table 6. Technical Efficiency Levels Based on Collective Action Participation

	Non-Group participants		Group participants	
Grouped TE Scores	Frequency	Percentage	Frequency	Percentage
0.5 ≤ 0.6	5	5.00	3	1.88
0.6 ≤ 0.7	22	22.00	16	10.00
0.7 ≤0 .8	12	12.00	27	16.88
0.8 ≤0 .9	7	7.00	26	16.25
0.9 ≤ 1.0	54	54.00	88	55.00
Total	100	100	160	100
Mean	.8561		.8854	

Source: Author's Calculations Using Tegemeo Institute Household Survey Data (2014).

For those farmers who did not participate in groups, it reached a point beyond which further increase in field size led to decrease in productivity. The result was obtained by squaring the field size whereby only collective action participants showed positive elasticity at 1% significance level. Apart from land size, organic manure and inorganic fertilizer also showed a significant effect on banana productivity. High quantity of organic manure showed 0.1 elasticity level for non-collective action members at 1% significance level. Use on organic manure did not show a significant effect among the group members. However, the use of inorganic fertilizer was seen to have significant effect on the productivity among collective action members. A unit increase in the use of inorganic fertilizer in banana crop showed high positive elasticity for non-group members at 1.18 compared to 0.35 for the group members. However, the significant effect was realized when quantity of the fertilizer reached certain substantial levels which result in 12% returns to scale for group participants as shown when the quantity is squared**.** In overall, the non-group members showed increasing total returns to scale from resource use at 2.22 whilst their group counterparts showed decreasing returns to scale at 0.77.

The overall mean of technical efficiency was estimated at 0.87, collective action participants had higher mean efficiency level (0.89) compared to non-participants (0.86). The field size had significant influence in productivity levels for both collective action participants and non-participants at 1% level. For non-group participants, the elasticity for field size was 1.38, while for collective action members, field size showed lower elasticity of 0.42. The results of efficiency levels based on collective action participation are reported in Table 6. From the table, all the farmers had technical efficiency levels of above 50%. The results further showed that only 12% of farmers in collective action had technical efficiency levels below 27% compared to non-members. Only 19% of non-collective action members had technical efficiency scores of between 70% and 90% compared to corresponding 33% of collective action members (Table 6).

3.4. Hypothesis test for Difference in Mean Technical Efficiency Levels

H_O: The mean technical efficiency of group participants is not significantly higher than the one for non-group participant smallholder banana producers.

H_A: The mean technical efficiency of group participants is significantly higher than the one for non-group participant smallholder banana producers.

From Table 7, the null hypothesis was rejected at 95% confidence level. From the hypothesis test results, a banana farmer in group participation is likely to be more productive than non-participants at given level of available inputs. Group participation therefore significantly enhances a farmer's technical efficiency levels for better economic returns.

3.5. Determinants of Technical Inefficiency of Banana Production by Group Participation

Estimation of sources of technical inefficiency was done by second-stage estimation of MLE where household exogenous variables were incorporated in the model. The covariates that were used in the model included mainly household socioeconomic characteristics and group factors. The household factors used were household size, age of the household head, gender, occupation type, education level, off-farm income, marital status. The group factor incorporated in the model extension advice. Farmer's main occupation was subdivided into two categories - salaried occupation and business/informal occupation. It was expected that these factors would influence a farmer's decision, thus efficiency level.

From the descriptive analysis, the overall mean inefficiency level was found to be 0.113 which is more than mean for group participants (0.095) and less than mean inefficiency level for non-group members (0.141). The descriptive statistics of technical inefficiency are as shown in Table 8.

The results of the factors that contribute to inefficiency among smallholder banana producers were presented in Table 9. The effect of age on technical inefficiency was also similar for group participants in the study area, with both farmer categories experiencing adverse effects. Type of occupation of non-group members had significant effect at 10% level. The salaried occupation significantly showed increase in inefficiency whilst informal occupation had a significant decrease in inefficiency levels among the farmers. Gender of the farmers showed significant effect in inefficiency levels of group participants, where by male farmers were found to be more inefficient than female counterparts at 5% significant level.

Table 7. Hypothesis Test for Difference in Mean TE Levels by Group Participation

	Sample	Non-group members (X_I)	Group members (X_C)	mean difference X_C-X_I	t-value	P-value
N/n	260	100	160			
Mean	.874	.856	.885	.029**	3.018	.0015
S^2	.018	.022	.015			
S^2/n	.000	.000	.000			

Note: n= subsample size, N= total sample, S^2 = sample variance.
Source: Author's Calculations Using Tegemeo Institute Household Survey Data (2014).

Table 8. Descriptive Statistics for Technical Inefficiency Levels by Group Participation

	Observations	Mean(u)	Std. Dev	Minimum	Maximum
Total sample	260	0.113	0.1537	0.000	0.854
Non group members	100	0.141	0.186	0.000	0.854
Group members	160	0.095	0.127	0.000	0.659

Source: Author's Calculations Using Tegemeo Institute Household Survey Data (2014).

Table 9. Comparison of sources of Technical Inefficiency by Group Participation

	Non-group member		Group member	
Variable	Coefficient	Std. error	Coefficient	Std. error
Constant	-0.302	0.545	0.000	0.714
Household size	-0.569	0.460	0.193	0.346
Age of the farmer	-0.015***	0.004	-0.017***	0.012
Highest education level	0.003	0.009	0.004	0.031
Gender	-0.079	0.141	-0.010**	0.178
Marital status	0.383	0.277	0.000	0.527
Salaried occupation	0.289*	0.154	0.033	2.69
Informal occupation	-0.290*	0.154	0.001	0.009
Access to extension service	0.016	0.144	0.060	2.546
Off-farm income (KES.)	0.000	0.000	-0.000	0.000
Total asset value (KES.)	0.000	0.000	-0.000	0.000
Amount of credit received	0.000	0.000	-0.000	0.000
Total observations	100		160	

Legend: * p<.05; ** p<.01; *** p<.001.
Source: Author's Calculations Using Tegemeo Institute Household Survey Data (2014).

4. Discussions

The Logistic regression model in the first objective shows pseudo $R^2 = 0.47$ which is a good model fit [28]. From the regression results, various factors which influence group participation by the smallholder banana producers show consistency with various findings from other previous studies. For instance, age had a positive effect on likelihood of group participation. This can be explained in relation to choice for farming as occupation which has a negative correlation with farmer's age. The majority of younger population always tend to disregard farming as a source of employment and instead move to urban areas to seek for alternative sources of income. A relatively larger proportion of older population are left in the rural areas engaging in farming as part of their main occupation, thus higher likelihood of finding older farmers dominating agricultural production related groups [16,17,29]. The finding was consistent with similar findings of most of earlier studies which found age to be positively correlated to likelihood of group participation. According to [13,16,29,30], majority of younger population preferred to look for other sources of employment than engage in agricultural activities. From the result, it is clear that young people especially the male are yet to embrace agribusiness, or engage in agricultural activities as source of livelihood.

On gender, female farmers were strongly associated with collective action than their male counterparts. This could be attributed to the fact that, in Kenya banana production has been highly associated with women, therefore it was expected that most of the farmers participating in groups would be female farmers [11]. Moreover, previous studies have found female farmers to be more likely to participate in collective action compared to male counterparts. Women prefer to build more social ties than men which motivate them to engage in collective action [29]. There was positive association between education level of the farmer and likelihood of group participation which was consistent with other results from previous surveys. In [29], relatively more educated farmers are more likely to engage in group participation as education increases individual awareness of the benefits associated with collective action. Also, educated farmers are more knowledgeable and understand the important role collective action entities play in trying to improve small-holder individual farmer productivity, thus they are more likely to seek for such organizations [10]. The salaried occupation had a statistically significant adverse effect on group participation at 5% level. The negative impact of salaried occupation on group participation could be attributed to the opportunity cost of time. It should be noted that most salaried individuals are employees under strict rules. Therefore the majority of such employees do not find time to attend group meetings. Additionally, salaried employees are relatively more likely to access credit facility as individuals using pay slips as security as opposed to those farmers involved in informal income activities. On the other hand, farmers in informal businesses and other casual work (*vibarua*) have the incentive to engage in collective action to benefit from social capital to enhance chances of access to inputs, credit facility, and information [10].

Regarding information access, the study found that mobile phone ownership had a positive and significant effect on the likelihood of banana group participation at 1%. This is plausible because a farmer who owns a mobile phone can access information easily regarding scheduled meetings. According to [13,30], banana producers who own mobile phones are easy to be contacted and given information regarding group formation, and notification about group meetings. Finally, access to extension advice increased the probability of collective action participation by a household at 1% significant level. Groups which provide easy access to extension advice attracts more members because it reduces the cost of information access and at the same time enhance farmer's awareness and informed decision making during production [11].

The determinants of productivity were estimated in a truncated normal distribution of MLE. From the model, gamma was estimated at 0.092 and 0.022 for the group and non-group participants respectively. The low levels of gamma imply that the deviations in banana output are huge as a result of factors other than inefficiency in input use by smallholder farmers. The factors are believed to be random shocks which are beyond the control of the farmer such as climatic factors, pests and disease infestation and statistical errors [22]. From the gamma estimates, it could

be seen that non-collective action participants are more susceptible to effects of random shocks than their counterparts who subscribe to collective action. The result was expected because group members are likely to gain more and better skills in dealing with prevailing adverse climatic conditions and any other uncertainty in the course of production [22].

The size of banana fields had a positive significant influence in productivity levels for both collective action participants and non-participants with 1.38 and 0.42 elasticity of production respectively. The positive elasticities show consistency with other previous literature on effect of land size on farmer technical efficiency levels where productivity levels showed positive relations with increase in land size [18]. However, by squaring the field size only collective action participants showed positive elasticity. The difference can be attributed to variations in managerial ability between the two farmer categories as well as benefits due to collective action. As field size gets larger, it requires more managerial skills and mechanization which most smallholder farmers cannot afford [30]. This prevents farmers from full utilization of the field capacity. Collective action participants enjoy extra human capital apart from family labour, furthermore, they have access to information on better management practices and innovative ideas. Use of high quantities of organic manure showed 0.1 elasticity level for non-collective action members, whilst inorganic fertilizer was seen to have significant effect on the productivity among collective action members. The significant effect was only realized when quantity of the fertilizer reached certain substantial levels which result in 12% returns to scale for group participants as shown when the quantity is squared. The findings corroborate with previous findings, where by the use of fertilizer was found to yield significant returns when the quantities are sufficient enough [18,20].

The results of technical efficiency estimates revealed a huge discrepancy in technical efficiency levels among non-collective action members. This was expected bearing in mind that these farmers are more interested in individual goals and selfish interests without caring about others. For the collective action members, the findings conform to the underlying roles of collective action in the game theory, whereby one of the objectives of collective action by farmers is to help in achieving collective goals together [14]. The hypothesis test results showed that, a banana farmer in a group is likely to be more productive than the one in no group at a given level of available inputs, thus enhanced farmers technical efficiency levels for better economic returns. The results conform to previous studies which have shown that collective action participation makes individual farmers more efficient in decision making and management of farms which are likely to impact positively on-farm technical efficiency levels. According to [20], farmers who participate in collective action are likely to be less inefficient technically because they are more likely to enjoy better access to production information and other production-related support from such groups. In addition, that collective action enhances smallholder farmer's ability to strengthen their bargaining power, enhance their access to credit and innovations as well as associated farm management skills, which could foster reduction in their inefficiency levels [7]. Collective action is also likely to provide farmers with opportunity to receive mutual support which in times of need which eventually reduce technical inefficiency.

From the model, a significant effect was shown by age and occupation type among non-group members, whereby older farmers were more efficient than younger ones. The effect could be attributed to their accumulated experience over the years which equipped them with better farming ideas than their younger counterparts. The effect of age on technical inefficiency was also similar for group participants in the study area. The results were consistent with what happens in the ground whereby the older farmers embrace collective action participation. Consequently, in addition to their accumulated experience over the years, they have better access to new farming technologies and innovations which they obtain from the groups [30]. Moreover, they are more likely to obtain production inputs and access credit facilities offered by the groups. Thus improves their technical efficiency, compared to the younger farmers. The correlation between age and technical inefficiency is consistent with earlier findings, where older farmers embrace group participation [13]. By disregarding collective action, the majority of the younger farmers miss out on important innovations and information which could enable them improve their efficiency. Instead, they continue repeating the inefficient ways of farming and poor decision making over and over, thus increasing their inefficiency. This is consistent with the finding in [20], which found older cocoa farmers in Ghana to be less inefficient than the younger ones. However, [19] found younger farmers to be less inefficient in maize and fruit production systems than older counterparts in Cameroon.

The salaried occupation significantly showed increase in inefficiency, whilst informal occupation had a significant decrease in inefficiency levels among the farmers. First, this could be attributed to the fact that salaried employees spend most of their time in providing service to their employers. This leaves them with no time to spend in managing their farms. Second, salaried workers who employ others in the farm indicated during the interviews that they spent very little time with farmworkers, thus they have no time to effectively monitor farm operations; a scenario which is likely to cause principal-agent problem. On the other hand, informal occupation enables a farmer to get time to monitor farm work as well as manage operations on the farm, thereby reducing inefficiency. Gender of the farmers showed a significant effect in inefficiency levels of group participants, whereby male farmers were found to be more inefficient than female counterparts. This can be explained by the fact that banana production still remains a female-dominated activity with very little male contribution. For this fact, female farmers are more motivated to seek efficient ways of producing the crop than male ones which explains the difference in inefficiency levels. The finding was however not consistent with other studies which found that male farmers are likely to be less inefficient than female counterparts [19,20].

5. Conclusions

With the main objective of determining the effect of collective action participation on technical efficiency of

smallholder banana producers in Kisii and Nyamira Counties, Kenya, stochastic production frontier model was used to estimate technical efficiency levels and factors which cause inefficiency among farmers based on group participation. The study used a sample size of 260 farmers across the two counties with 160 of the sampled farmers belonging to collective action. From the results, the farmers were generally found to be producing below optimum efficiency level at 87%. Group participants, however, had a higher mean of 89% compared to 85% of their counterparts. The mean difference was significant at 5% level. The results show that banana farmers can be more efficient if they join groups. It was also noticed that there seems to be a high discrepancy on efficiency scores for the non-collective action members compared to collective action members.

There is an established similarity between factors that influence collective action and those which affect technical inefficiency among farmers. This proves that addressing various socio-economic, physical and technical challenges would be important in resolving farmer inefficiency problems. The fact that the results of production frontier model revealed that most of the variations in banana productivity was due to random shocks for both farmer categories, it can be concluded that the higher efficiency levels of farmers in production groups was as a result of the role groups play in helping smallholder farmers to cope with or resolve these challenges. Consequently, this enables group participants improve their technical efficiency in banana production. In establishing the determinants of collective action participation where logit regression revealed that female farmers embraced group participation, whilst male farmers showed little attraction to farmer groups. Education level was also found to favour group participation as it increases one's awareness and understanding of the importance of collective action. Group membership is also associated with low-income earners and informal employees. Evidently, those farmers who get relatively higher off-farm income were reluctant to join production groups because they feel they will be over-relied on to fund group activities. The results obtained from the study, however showed few contradictions with some previous literature which calls for further research to give more consistent findings and reliable conclusions.

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Statement of Competing Interests

The authors have no competing interests.

List of Abbreviations

AEZ	Agro-Ecological Zones
DEA	Data Envelopment Analysis
DRA	Development Regimes for Africa
EPSEM	The process was done using Equal Probability Selection Method
FARA	Forum for Agricultural Research in Africa
FAO	Food and Agriculture Organization
GDP	Gross Domestic Product
KNBS	Kenya National Bureau of Statistics
MLE	Maximum Likelihood Estimation
MOA	Ministry of Agriculture
NASSEP	National Sampling Survey Evaluation Program
TAPRA	Tegemeo Agricultural Policy Research Analysis
TC	Tissue Culture

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