Is Micro-Finance Achieving Its Goal Among Smallholder Farmers in Africa?

Empirical Evidence from Kenya Using Propensity Score Matching

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Abstract

With access to formal credit proving almost impossible to smallholder farmers, group based lending is steadily becoming popular in Africa. However, little is documented on the role of such programmes. In this paper, we employ propensity score matching method to evaluate effects of micro-finance credit (MFC) on borrower's productive performance in Kenya. Our findings reveal that participation in MFC credit improves household productive incomes by a range of between US$ 200 and US$ 260 in a single production period. However, participation in the MFC among smallholder farmers is constrained by low literacy levels, gender differentials in asset endowment, poor road infrastructure, and maintenance of indigenous group structures as key factors for policy intervention.

Key words: Micro-Credit, Smallholder-Farmers, Performance

1.0 Introduction

Like most Sub-Saharan Africa, Kenya depends to a great extent on the growth of the rural sector, where over 60% of the population lives, with agriculture as their mainstay. Agricultural sector accounts for 24.2% of the country's Gross Domestic Product (GDP), over 60% of exports, employs 75% of the total labour force, and provides 80% of industrial raw materials (RoK, 2006). In support of desired growth the country have developed vision 2030, which emphasizes the transformation of the country into a newly industrialized nation through linkages between agriculture and financial sectors as twin engines for achieving that vision. Efforts, therefore, to improve and sustain the sector's productivity remain crucial to the nation's economic development and the welfare of her people.

However, one of the major constraints in achieving this goal has been growing imbalances in credit demand and supply, among the majority smallholder farmers. Studies conducted in Kenya (Salasya, *et.al*. 1996; Hassan, 1998; 2000; De Groote *et al*. 2001; Odendo, *et. al*, 2002) point at inadequate smallholder credit as the main impediment to adoption of improved production methods and growth of the rural areas. Accessing loans from formal financial institutions has proved almost impossible. This has led to emergence of Grameen type Micro-Credit Institutions that lend through groups to overcome collateral problems (Hossain, 1988; Mosley, 1996; Ouma, 2002). Zeller *et al.(*2002) and Ghalak, (1999) supports this model as it has an important feature of forming groups that attach savings to creditworthiness, with peer pressure and membership restrictions, which replace the need for legal collateral.

The success of the model has fostered numerous replications around the world, Kenya being a good example. Organizations using this model in Kenya include Promotion of Rural Initiatives and Development Enterprises Ltd (PRIDE), Kenya Women Finance Trust (KWFT), Faulu Kenya, Kenya Rural Enterprise Programme (K-Rep), Women Development Company (WEDCO), Small and Micro Enterprise Programme (SMEP), Family Finance and many others (RoK, 2006). Nonetheless, there have been concerns by many authors; Paxton *et. al*. (2000); Zeller, (2000) and Onyuma et al, (2005) on whether replications of the model in African socio-economic environments result in the same impact. It is on this ground that this study ventured to establish impacts of Grameen based micro-credit programmes being wholesomely transferred into Kenyan socio-economic environments, particularly among the resource poor smallholder farmers.

2. Methods

2.1 Study Area and Sampling

The study covered two districts in Kenya, namely Nakuru district which falls in the high tropics and Kakamega district in the Low tropics. The high tropics region is characterized by high yields and viewed as the bedrock of food security in Kenya. Presence of credit groups and micro-finance institutions here dates back to mid 1990 following government efforts to promote micro-lending across farm and non-farm micro-entrepreneurs. Low tropics region of Kakamega is located around the Lake Victoria. This area is categorized as Moist Mid-altitude (MM) zone (Hassan, 1998). It is characterized by moderate yields, with high poverty levels (65% of households living below 1 US$ per day) (RoK, 2006). The two contrasting districts are used to act as representatives of similar environments in the country

2.2 Sampling and Sample Design

A multi-stage random sampling methodology was used to arrive at a total sample of 400 smallholder farmers. The selection of the sample was based on proportionate to size sampling approach as: $n = (Z\ 2PQ) / d\ 2$. ….. 1. Where, *'n'* is the sample size 'Z'=1.96, *'P'* is the proportion of the population of interest ie. smallholder farmers who access credit through group based sources, which stand at approximately a half of smallholder farmers population following previous studies. Besides, statistically a proportion of 0.5 results is sufficient and reliable size, particularly when the population proportion is not known with certainty (Daniel, et al, 1975). The variable'*d*' is the significance level and is set at 0.05

because 95% confidence level was used as a cut off point for significance in this study. This also leads to *'Z'* value of 1.96. Variable *'Q'* is the weighting variable and is computed as *1-P*. Therefore, based on the above methodology the sample size proposed was: [1.962 x 0.5 x 0.5] / [0.052] = 385. However, this figure was approximated to 400 to conveniently meet the sampling procedure.

The sampling procedure was as follows; in the first stage, a purposive sample of 2 districts was made, while in the second stage a stratified random sampling of 40 credit groups (20 per district) was then selected. Out of the 20 groups, 10 were those that participated in borrowing from MFIs, while the other 10 were those who did not. Finally, in stage three, 10 members from each of the groups were randomly selected, making a total of (1 x 20 x 10) = 200 per district. The list of groups was obtained from the Ministry of Culture and Social services and Community development officers operating within the districts.

2.3 Conceptual and Analytical Approach

In a typical farm production, income can only be realized a short period after harvest, yet expenditures on purchased inputs must be made in cash prior to the harvest. The availability of a adequate credit allows greater purchased inputs and thus higher output performance. However, asymmetric information, adverse selection and contract enforcement problems that characterize credit markets in developing countries usually prevail giving rise to credit rationing as an optimal behaviour limiting expected gains in credit (Stiglitz and Weiss, 1981; Ghosh, Moorkerjee and Ray, 1999). In this paper, we employ propensity score matching to evaluate marginal impact of group based lending programme (that uses Grameen lending approach) on smallholder farmers' productive performance as measured in total income from productive activities.

Rosenbaum and Rubin (1983) pioneered propensity score matching followed by many other improvements and applications in works by Dehejia and Webba (1999; 2002), Becker and Ichino, (2002) and Caliendo and Kopeinig, (2005). They defined propensity score as conditional probability of participation given pre-participation characteristics of the subject. Their argument is based on the fact that since assignment of subjects to participation and control groups in a given programme may not be random, then estimation of the effect of participation may be biased by the existence of confounding factors.

Therefore, they proposed propensity score matching as a away to correct for the estimation of effects of the programme controlling for the existence of these confounding factors based on the idea that the bias is reduced when the comparison is performed using participants and control subjects who are similar as possible. To achieve this, the method summarizes pre-participation (pre-participation) characteristics into a single index known as propensity score, which makes matching feasible. Propensity score is a conditional probability estimator, and any discrete choice model such as logit or probit can be used as they yield similar results (Caliendo and Kopeinig, (2005. The matching estimators used are nearest neighbor, radius, kernel and stratified matching methods all conditional on propensity score. The propensity score model is expressed as:

$$p(X_i) \equiv pr\{D = 1 / X_i\} = E\{D / X_i\} \text{-------------} (2)$$

Where D= (0, 1) is a participating variable (in this case borrowing status) and X_i is a vector of pre-participation covariates. Propensity score ensures that matching estimation is done on subjects that are similar as possible for effective comparison. As a result, given a population of units denoted by (i), if the propensity score $p(X_i)$ is known the Average Effect of Participation (AEP) can be estimated as:

$$AEP \equiv E\{Y_{1i} - Y_{0i} / D_i = 1\} = E\{E\{Y_{1i} / D_i = 1, p(X_i)\} - E\{Y_{0i} / D_i = 0, p(X_i)\} / D_i = 1\} \text{ - (3)}$$

Where (AEP) is the average effect of participation, Y1i and Y0i are the potential outcomes for the two counterfactual situations of participation and non-participation respectively, p(Xi) is the propensity score, D is the participation variable, where D=1, if participated and 0 otherwise. This model works under two assumptions; the balancing assumption and conditional independence assumption. The balancing assumption postulates that participation is shaped by pre-participation characteristics. Conditional independence assumption postulates that all the covariates must be independent of participation.

2.4 Evaluation of Average Effect of Participation

Four approaches have been proposed, nearest neighbor, radius, stratified and kernel matching. Nearest neighbor matching uses random draw with replacement or without replacement. In the former, a control individual is used more than once as a match, whereas in the latter case it is considered only once. We use matching with replacement following routines similar to ones employed by Backer and Ichino, (2002). Nearest neighbor match is computed as follows $C_i = \min_j \|p_i - p_j\|$ …… 4. Where Ci is asset of control units matched to the treated unit (i), with estimated value of the propensity score *pi* . Radius matching on the other hand is where an individual from the control group is chosen as a matching partner for a participant that lies within the specified radius in terms of propensity score. Radius matching can be expressed as

$C_i = \{p_j \| \|p_i - p_j\| < r\}$ ----5, that is to say, all propensity scores for controls (*pj)* falling within a radius (r) from *pi* (propensity score of participant, i) are matched to that participant (i). Stratification matching method uses blocks of common support to compute average effect of the programme on participants. It involves partitioning of the common support of the propensity score into a set of intervals, and then calculating the impact of the programme within each interval by taking the mean difference in outcomes between participants and control observations. Aakvik, (2001) and Caliendo and Kopeinig, (2005) show that five strata are often enough to remove 95% of the bias associated with one single covariate. The formulation within each stratum is computed as:

$$AEP_q^S = \frac{\sum_{i \in I(q)} Y_i^P}{N_q^P} - \frac{\sum_{j \in I(q)} Y_j^C}{N_q^C} \text{ ------------------------ (6)}$$

Where I (q) is the set of units in block q while N_q^P and N_q^C are the numbers of participants and control units in block q. The AEP for all the strata are then averaged to arrive at total samples' AEP. In the case of Kernel Matching (KM), each participant is matched with a weighted average of all controls with weights that are inversely proportional to the distance between the propensity scores of participants and controls. The formulation is given as

$$ATT^K = \frac{1}{N^T} \sum_{i \in T} \left\{ Y_i^T - \frac{\sum_{i \in c} Y_j^c G\left(\frac{p_j - p_i}{h_n}\right)}{\sum_{k \in c} G\left(\frac{p_k - p_i}{h_n}\right)} \right\} \text{ ------------------------------ (7)}$$

Where G (.) is a kernel function and h_n is a bandwidth parameter (default is 0.06), Under standard conditions on the bandwidth and kernel the following expression is a consistent estimator of the counterfactual outcome Y_{0i}

3. Results and Discussion

3.1 Structures of Group-Based Micro-credit Lending and loan monitoring

The general trend among MFC institutions is that they lend via credit groups, with loan applicants guaranteeing each other through collective liability. MFC charges interest rates that range between 5-7% per month, with repayment periods of between 3 months to 1year. Loans are graduated, with first loans ranging between US$ 220 and US$ 260. Loan applications are staggered with successful repayments leading to access to higher subsequent loans, usually twice as much as the first loans. Screening of potential loan beneficiaries is done using group information about applicant's socio-economic history such as character, previous repayment records and savings status.

3.2 Factors that influence Probability of Participating in Micro-credit

Among the hypothesized factors education, exposure to agricultural seminars, female gender, off-farm engagement, and access to other sources of credit had positive and significant effect on marginal probability of participating in the micro-finance credit programme. On the other hand, the higher the number of older members per household, larger group sizes in terms of membership and location further a way from the market significantly reduced the marginal probability of participating. Table 1 shows these results

Table 1: Marginal Effects for Factors that Influence participation in MFI-Credit

Predicted probability of Y	0.447	N=401			LR X^2		101***
Log likelihood	-225				Pseudo R^2		0.283
Dep: if MFI participant (Yes=1, No=0)	dy/dx	Std. Err.	z-test	P>|z|	95%	C.L.	X
Age of head (Yrs)	0.002	0.003	0.7	0.483	-0.03	0.007	44.15
Head Education (Yrs)	0.023	0.007	3.58	0.000	0.011	0.036	8.998
If attended seminar (1,0)	0.209	0.062	3.35	0.001	0.087	0.331	0.249
If head is female (1,0)	0.161	0.06	2.66	0.008	0.042	0.279	0.641
Hld members below 20 yrs	-0.017	0.012	-1.4	0.161	-0.04	0.007	2.895
Hld members aged 21-49 yrs	0.029	0.014	2.06	0.039	0.001	0.056	2.379
Hld members>50 yrs	-0.124	0.038	-3.3	0.001	-0.19	-0.05	0.688
If own title to land (1,0)	-0.008	0.085	-0.09	0.927	-0.17	0.159	0.845
If received transfers (1,0)	-0.057	0.058	-1.1	0.329	-0.17	0.057	0.364
Hrs on off-farm activity/daily	0.139	0.024	5.72	0.000	0.091	0.186	0.968
If borrowed other credit (1,0)	0.16	0.06	2.68	0.007	0.043	0.277	0.342
Members in a group	-0.003	0.002	-1.4	0.161	-0.01	0.001	26.89
Distance to market (km)	-0.005	0.003	-1.71	0.031	-0.01	0.001	4.92
AEZ (Nakuru=1, Kak=0)	0.065	0.063	1.02	0.306	-0.05	0.189	0.504

The significance of education is consistent with conventional economic theory on the role of literacy in improving conceptualization of information and making economically viable decisions in financial markets. In support for the role of literacy, our results on exposure to agricultural seminar show similar effects. Results on female gender indicate immense involvement of women in rural economy as well as the fact that women get more attracted to MFC that peg no tangible credit to lending, reason being that a majority of women in Africa still lack right to property to hold as collateral against credit. For example, in Kenya traditional norms still limit inheritance of property by women, such that the creditworthiness of women in the face of formal financial institutions are diminished prompting a majority to shift their loan applications to group based financial markets, such as MFIs. The positive effects of time spent on off-farm activity can be viewed in the context of access to extra and regular income that complements loan servicing. Results on the number of older members of the household point at the low participation of old people in mandatory group savings. Besides, such households are likely to face labour supply problems, with consequential low incomes to commit to savings. The negative effects of group sizes are a possible indicator of collective liability problems. As group size becomes large, more difficulties emerge in reinforcing sanctions (Gine, and Karlan, 2006). Market distance indicates relative effects of transaction costs, a factor that constraints information access.

3.3 Average Effect of MFC on Smallholder Farmer's Productive Performance

The average effect of MFI credit was measured using four matching routines as specified in the methodology section, with results showing that Nearest Neighbor Matching (NNM) matched 180 MFC-participants to 71 non-participants, with average effect on annual productive incomes of US$ 641.50 per household. The results were significantly at 1% level. In a household made up of six members as in this survey, it translates to 0.30 additional dollars per person per day, implying that MFC reduced poverty levels by 30%. Radius matching was estimated with a default of 0.005, implying that all the nonparticipants with estimated propensity scores falling within a radius 0.005 from the propensity score of a given participant was matched to that particular participant. Following on this, results reveal that 150 non-participants were matched to 133 participants, with a significant difference in productive income of US$ 628.462. Kernel matching and stratified matching results show that all 180 participants matched all the 221 controls, with an average effect on productive income of US $ 478.30. In both cases, the measurements were significant at 1%, with t-values of 3.64 and3.74 respectively. See Table 2 for the matching results.

Table 2 : Effects of Participation in MFIs Credit on Productive Performance

Matching Method	Participants	Non-Participants	AEP (US$)	Std. Err.	z-value
Nearest neighbor	180	71	641.50	167.50	3.83
Radius (0.005)	133	150	628.50	151.40	4.15
Kernel (BW 06)	180	221	478.31	131.50	3.64
Stratified (5 Strata)	180	221	478.31	131.50	3.74

Matching findings above resonate similar ones in the East Asian countries. For example, work by Hossain (1988) show that Grameen Bank members realized incomes that were 28% higher than non-participants in all the 30 project villages under survey. Hashemi and Morshed (1997) also observed that the Grameen Bank not only reduced poverty, and improve welfare of participating households, but also enhanced borrowers ’capacity to sustain their gains over time. Remenyi and Quinones, (2000) reported similar findings in Indonesia, Sri-Lanka and India.

4.0 Conclusion and Policy Recommendations

Participation in MFI credit has significant gains in productive income with literacy, female gender, communication infrastructure and maintenance of indigenous group structures as key factors for policy intervention. Mobilizing more groups, particularly women groups would go further in improving information asymmetry and resolving collateral problems.

Besides, improvement of rural road infrastructure would have multiple impact of access to credit, labour and product markets. Last but not least, MFIs can consider issuing different credit products that meet both productive and consumptive motives to avoid fungibility of credit meant for production.

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