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Can Group Based Credit Uphold Smallholder Farmers Productivity and Reduce Poverty in Africa? Empirical Evidence from Kenya

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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 and endogenous switching regime methods on a sample of 600 smallholder farmers drawn from two agricultural regions in Kenya in 2007. The goal of the survey was to evaluate the economic impact of group based credit programmes on smallholder farmers' productive performance and poverty reduction in Kenya. Our findings reveal gains with significant impacts of group based credit on incomes in the range of 300 and 480 euros as well as via purchased inputs, with participation in such credit programmes significantly constrained by low literacy levels prevalent among a majority of rural farm households, influence of gender, with female headed households dominating in membership and little participation on the part of male headed households, poor rural access road infrastructure and constraints in group management resulting from lack of cohesion as the group grows in membership. These factors form the key recommendations for policy intervention to achieve sustainability of group based informal lending among farm households in Africa and other similar developing nations.

Key words: Informal Micro-Finance, Smallholder Farmers, Performance in Kenya

1 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. The Kenyan economy heavily relies on the growth of the agricultural sector which accounts for 24.2% of the country's Gross Domestic Product (GDP), over 60% of exports, 75% of the total labour force, and over 80% of industrial raw materials (RoK, 2006). In support of the sector, the Ninth National Development Plan (RoK, 2002) to transform the country into a newly industrialized nation by the year 2020 emphasizes on the firm linkages between agriculture and financial sectors as twin engines for faster economic growth. 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 the desired growth levels has been growing imbalances in credit demand and supply, particularly with respect to 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 agricultural credit as the main impediment to adoption of improved production methods and growth of the rural areas. Accessing loans for small-scale agricultural investments from formal financial institutions has proved almost impossible. This has led to emergence of Grameen type Micro-Finance Institutions (MFIs) that lend via rural groups to overcome collateral problems (Mosley, 1996; Ouma, 2002). The Grameen Bank model is one of a kind that utilizes group lending. This concept originated in 1976 in Bangladesh as an action-research project to test the hypothesis that if the poor are supplied with working capital, they can generate productive self-employment without further external assistance. According to this model households with as little as 0.5 acres of arable land qualify to take loans provided they form credit groups (Hossain, 1988). Zeller *et al.(*2002) and Ghalak, M., (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, Grameen-style replications around the world since mid 1980s (Hossain, 1988). The replications have been fast with widening loan portfolios, particularly in Africa (Paxton *et. al*. 2000). 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 (Mosley, 1996; RoK, 2006).

However, there have been concerns by many authors; Huppi and Feder, (1990); Paxton *et. al*. (2000); Zeller, (2000) and lately by Onyuma et al, (2005) on whether replications of the model in other socio-economic environments such as Africa result in the same impact. Other contentious issues in the rural agricultural development arena that creates more caution in the rural credit systems are the experiences Africa have had with the so called '***the green revolution***'. Green revolution was a success story from Asia, where reports indicate that it was driven by technical innovations in food production, in particular improved varieties and fertilizer. Here, the experience was a rapid increase in yields, with growth in food production that surpassed rapid population growth without any negative consequences (Evenson and Golin, 2003). In Africa too there has been similar success stories, but not without consequential problems. The increase in use of improved varieties (as in maize) has come with more production risks due to the vulnerability of these technologies to harsh local conditions such as pests, disease and weather. In effect, African farmers have to contend with another technology; the adoption of Genetically Modified Crops (GMC) in order to stay in production. In the face of this dilemma, it is worth noting that during the campaigns for green revolution farmers abandoned their local technologies for the improved ones, which turned to be more susceptible to tropical pests and diseases. GM technologies in food production has had hot debate on efficacy and health concerns prompting scientists to shift emphasize to conservation of the very local germplasms that farmers discarded during the green revolution campaigns; creating more dilemma.

It is on similar grounds that this study ventured to establish impacts of Grameen based micro-credit programmes being wholesomely transferred into African rural socio-economic environments. The questions addressed are whether such credit systems actually lead to increased productivity performance and possible reduced rural poverty among the resource poor smallholder farmers.

2 METHODS

2.1 Study Areas 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 below:

$$n = (Z^2 PQ) / d^2 \quad \text{...} \quad (1)$$

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: $[1.96^2 \times 0.5 \times 0.5] / [0.05^2] = 385$. 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 credit markets allows greater purchased inputs and thus higher output performance. If a producer has infinite liquidity base then production decisions will be independent from consumption decisions (Singh, Square, and Strauss, 1986). However, asymmetric information, adverse selection and contract enforcement problems that characterize credit markets in developing countries prevail giving rise to credit rationing as an optimal behaviour (Stiglitz and Weiss, 1981; Ghosh, Moorkerjee and Ray, 1999). When credit is rationed potential borrowers cannot obtain the amount of fund they desire creating liquidity problems with input use deviating from their optimal levels, and affecting production. Under such circumstances, the objective of borrowing is to bring input use closer to the optimal level, thereby increasing output. This potential gain in productivity is one motivation underlying credit programme interventions in many developing economies, particularly among the resource poor farm households in Africa. In the context of agricultural policy, the most important issue is the magnitude of the expected productivity gain. If the marginal productivity of such credit programme is insignificant, then it would be advisable for such credit resources to be diverted to other sectors where it would be more economically beneficial. In this paper, we employ propensity score matching and switching regime methodologies to evaluate marginal impact of group based lending programme (that uses Grameen lending approach) on smallholder farmers' economic performance as measured in total income from productive activities.

2.3 Propensity Score Matching Method

Rosenbaum and Rubin (1983) pioneered propensity score matching methodology, followed by many other improvements and applications in works by Dehejia and Webba (1999; 2002), Becker and Ichino, (2002) and Caliendo and Kopeinig, (2005). Rosenbaum and Rubin defined propensity score as conditional probability of treatment given pre-treatment characteristics of the subject. Their argument is based on the fact that since assignment of subjects to treatment and control groups in a given programme may not be random, then estimation of the effect of treatment may be biased by the existence of confounding factors. Therefore, they proposed propensity score matching as a away to correct 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-treatment (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), even though logit distribution has more density mass in the bounds. This study employs logit model in its estimation, assuming logistic distribution of the sample means and variance. 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:

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

Where (AEP) is the average effect of participation, Y_{1i} and Y_{0i} are the potential outcomes for the two counterfactual situations of participation and non-participation respectively, $p(X_i)$ 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 or that the balancing of participants and controls is through the propensity score. Therefore, if *p(*X) is the propensity score then $D \perp X_i / p(X_i)$ ------------------------------ (4), ie the exposure to the programme (D) is shaped by the pre-participation covariates (X_i). The balancing assumption is thus the propensity score $P(D = 1X_i) = P(X_i)$. Conditional independence assumption on the other hand assumes that selection is based on observable covariates of the subjects and that all covariates that influence participation and potential outcomes are simultaneously observed. It is expressed as:

$$Y_{1,} Y_0 \perp D / p(X_i) \text{ --------------------------------- (5)}$$

Where, $Y_{1,}Y_0$ are the potential outcomes with and without the programme, D is the participation variable, P (X_i), is the propensity score. In other words, for a given propensity score, exposure to the programme is random and therefore participants and control households should be on average observationally identical (Caliendo and Kopeinig, 2005).

2.4 Evaluation of Average Effect of Participation

Nearest Neighbor Matching

This approach is whereby each participant is matched with control individual that is closest in terms of propensity score. This approach uses random draw with replacement or without replacement. In the former case, a control individual is used more than once as a match, whereas in the latter case it is considered only once. The choice of matching with replacement or without replacement depends on the data as whether propensity score distribution is very different in the participants and the control group. For example, if there are many participants with high propensity scores but only a few control individuals with high propensity scores, one is likely to come up with bad matches as some of the high-score participants may be matched to low-score controls. This can be overcome by allowing replacement, which reduces the number of distinct controls used to construct the counterfactual outcome and thereby increases the variance of the estimator (Smith and Todd, 2005). In addition, nearest neighbor matching depends on the order in which observations are matched. Hence, this approach requires that sorting of data by propensity index is done before matching (Caliendo and Kopeinig, 2005). We use matching with replacement following routines similar to ones employed by Backer and Ichino, (2002). Nearest neighbor match is computed as follows: $C_i = \min_j \left\| p_i - p_j \right\|$, Where C_i is asset of control units matched to the treated unit (i), with estimated value of the propensity score p_i .To complement this method other matching techniques are used such as radius matching.

Radius Matching

In radius matching 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. A benefit of this approach is that it uses only as many comparison units that are available within the predefined radius and thus allows for usage of extra units when good matches are available, and reduce the risk of numerous bad matches as may occur in nearest neighbor matching. However, one limitation is the difficulty in establishing a priori what choice of radius would be optimal. Radius matching can be expressed as $C_i = \{p_j \| p_i - p_j \| < r\}$, that is to say, all propensity scores for controls (p_j) falling within a radius (r) from p_i (propensity score of participant, i) are matched to that participant (i). The formula for matching both nearest neighbor and radius can then be written as

$$
\begin{aligned}
AEP &= \frac{1}{N^P} \sum_{i \in P} \left[Y_i^P - \sum_{i \in C_i} w_{ij} Y_i^c \right] \\
&= \frac{1}{N^P} \left[\sum_{i \in P} Y_i^P - \sum_{i \in P} \sum_{i \in C_i} w_{ij} Y_i^c \right] \\
&= \frac{1}{N^P} \sum_{i \in P} Y_i^P - \frac{1}{N^P} \sum_{i \in C_i} w_{ij} Y_i^c \text{ ------------------------------------- (6)}
\end{aligned}
$$

Where AEP is the average effect of the programme $i \in P$ is the number of controls matched with participants, w_{ij} are the weights which is $\frac{1}{N^C}$ if unit j is a member of the controls that matched the treated and w_{ij}=0 otherwise.

Stratification matching method

Stratification matching method uses strata or 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 or strata, and then calculating the impact of the programme within each interval by taking the mean difference in outcomes between participants and control observations. The number of strata to be used is usually the main challenging factor. However, 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. In this sense provided the common support condition is met with a minimum of 5 blocks, then, the same blocks can be used in stratified matching. In addition, as is pointed out in Imbens (2004); unconfoundedness is associated with the propensity score implying that under rational decision making one can specify at least a minimum of five strata from the propensity score estimation. The formulation within each stratum is computed as:

$$AEP_q^S = \frac{\sum_{i \in I(q)} Y_i^P}{N_q^P} - \frac{\sum_{j \in I(q)} Y_j^C}{N_q^C} \text{ ------------------------ (7)}$$

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.

Kernel matching method

With 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. Kernel matching is a non-parametric estimator that uses weighted averages of all individuals in the control group to construct the counterfactual outcomes. One major advantage of this approach is the lower variance which is achieved because more information is used. Hence, the proper imposition of the common support condition is of major importance for Kernel Matching (Heckman, Ichimura, and Todd, 1998). When applying KM one has to choose the kernel function and the bandwidth parameter. A high bandwidth-value yield a smoother estimated density function, therefore leading to a better fit and a decreasing variance between the estimated and the true underlying density function. The bandwidth choice is therefore a compromise between a small variance and an unbiased estimate of the true density function. The formulation is given as

$$ATT^{K} = \frac{1}{N^{T}} \sum_{i \in T} \left\{ Y_i^T - \frac{\sum_{i \in c} Y_j^c G\left(\frac{p_j - p_i}{h_n}\right)}{\sum_{k \in c} G\left(\frac{p_k - p_i}{h_n}\right)} \right\} \text{------------------------------} \quad (8)$$

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}. Stata version 8.2 is used to arrive at the above estimators.

2.5 Endogenous Switching Regime Model

To estimate the effect of borrowing on output via purchased factors we employ endogenous switching regime model. Since credit is an indirect input into production process, factoring borrowing directly into a production function would lead to endogeneity problem. Besides, credit is also exogenous to purchased factors such as fertilizer and hired labour in the same function. Therefore, inclusion of borrowing directly would lead to biased estimates. To resolve this dilemma, we employ endogenous switching regime model as in Madalla (1993); Greene, (2003) and used by Main and Reilly (1993), and Millimet (2003). We begin by expressing the general output function with credit variable as follows:

$$Y = \lambda_i D_i + \beta_i X_i + \varepsilon_i \text{ ....} (9)$$

Where Y is the outcome, D is a dummy whereby D=1 if borrowed, D=0, otherwise, X_i is a vector of conventional production factors, which include purchased inputs and other socio-economic factors. In the above function, D is endogenous to Y, and exogenous to some of the X_i covariates. Therefore, the model involves splitting the sample into borrowers and non-borrowers and then estimating the structural equations for each sub-sample as follows:

$$\left.\begin{array}{l} y_1 = \beta_{1i} X_{1i} + \varepsilon_{1i} \\ D = \gamma_i Z_i + \varepsilon_i \end{array}\right\} iff D > 0 \quad \text{For the borrowers sub-sample................(10)}$$

$$\left.\begin{array}{l} y_2 = \beta_{2i} X_{2i} + \varepsilon_{2i} \\ D = \gamma_i Z_i + \varepsilon_i \end{array}\right\} iff D \leq 0 \quad \text{for the non-borrowers sub-sample ....(11)}$$

Where; y_1 and y_2 are the outcomes for borrowers and non-borrower's sub-samples respectively. X_{1i} and X_{2i} are the conventional factors that influence outcome functions for borrowers and non-borrowers respectively. D is a dummy (D=1, if borrowed and D=0, otherwise), Z_i is a vector of conditional covariates that influence the probability of participating in the borrowing programme. $\beta_{1i,}$ β_{2i} γ_i are the corresponding vectors of parameters and ε_{1i} ε_{2i} ε_i are random disturbances. The (y) variables are observed conditional on the unknown criterion determined by the D function, which is estimated via a probit model to yield γ_i estimates. The estimated γ_i are then used to generate mills ratios, which are incorporated in the second stage estimates where equations y_1 and y_2 with their mills ratio corrections are estimated using heckman two-step routines to yield average production estimates. Under the model assumptions, the estimated coefficients are efficient and asymptotically normal. Essentially this model allows for the full set of interaction terms between borrowing status and factors of production, particularly the purchased factors. Besides, it allows evaluation of the contribution of credit among other factors in production and the marginal differences of coefficients in purchased factors can be attributed to the contribution of borrowing to production. An alternative to switching regime model, but which would yield similar results is Two Stage Method of Moments (TSM) (Miranda, 2003).

3 RESULTS AND DISCUSSION

3.1 Factors that Influence Participation in MFI Credit

In reference to the above assumptions, this sub-section presents results of the factors hypothesized to influence participation in MFI-credit. Model specification results show that all significant variables hypothesized met the cut off point of 5% significance level (see Table 1). In addition, the chi-square (X^2) statistics stood at 100 and was significant at 1%, indicating the significance in the explanatory powers of the variables included in the model. The Pseudo R^2 was also 28%, higher than the cut-off point of 20%, implying that a high percentage of the changes in the dependent were associated with the variables in question. The covariates show marginal changes in the predicted probabilities of participation in MFI-credit. Presentation of marginal probabilities enables ease in the interpretation of the covariates, and reflects marginal changes of the dependent due to a unit change in the covariates.

Further, results show that formal education, attendance to agricultural seminars, female gender, time-spent daily on off-farm activity and access to other sources of credit significantly increased the marginal probability of a household participating in MFI credit. On the other hand, the number of household members aged above 50 years and distance to the market, significantly reduced the marginal probability of a household participating in MFI-credit, see Table 8. Detailed interpretation and discussion of each variable follow the table.

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

3.2 Estimates of Average Effect of MFI credit on Beneficiaries' Performance

This section presents results of propensity score matching discussed in chapter three. The findings present the average effect of participation in MFI borrowing on household's annual income from all productive activities. These were incomes generated during the production period 2005, immediately after borrowing. Results are presented in Table 2 and interpretations together with discussion of the results broken into different matching approaches, namely nearest neighbor, radius, kernel and stratified matching.

Results on Nearest Neighbor Matching (NNM) show that all the 180 participants matched 71 non-participants, with average effect of participation on annual productive incomes of Ksh. 48,113.24 per household. The results were significantly different at 1% level with a t-value of 3.83. Distributed on a monthly basis translates to an average of Ksh. 4,000 difference in income between participants and non-participants. In a household made up of six members as in this survey, it translates to 22 additional Kenya shillings per person per day. This implies that MFI credit could reduce poverty levels by 30% of a dollar by the time of survey (1 US$ = Ksh. 75.00).

Radius matching was estimated with a default of 0.005, implying that all the non-participants 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 matched 133 participants, with a significant difference on productive income of Ksh 47,134.65, t-value of 4.15 and p-value of 0.001.

Kernel matching and stratified matching results show that all 180 participants (borrowers) matched with all the 221 non-participants (non-borrowers), with an average effect on productive income of Ksh. 35,873.25. In both cases, the measurements were significant at 1% level, with t-values of 3.64 and 3.74 respectively.

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

Matching Method	Participants	Non-Participants	AEP (Ksh)	Std. Err.	t-value
Nearest neighbor	180	71	48,113.24	12,562.15	3.83
Radius	133	150	47,134.65	11,354.68	4.15
Kernel	180	221	35,873.25	9,863.50	3.64
Stratified	180	221	35,873.25	9,592.85	3.74

Paying attention to all the matching results, one observes a general positive effect of participation in MFI credit on households' productive incomes in the range of Ksh 35,873 and Ksh. 48,113 in one production period. All the four measurements were significant at 1%, indicating the important role MFIs credit plays in improving economic performance of rural resource poor farm households. According to Backer and Ichino, (2002), a combination of any three of the matching approaches (Nearest Neighbor, Stratified and Kernel) should be adequate to arrive at a reliable conclusion on the relative effect of the programme. On this breath, results from this survey lead to a strong conclusion on significant and positive effect of MFI-credit on economic performance of smallholder farmers in Kenya.

One major challenge that could face MFIs operating among the rural communities in Kenya is sustainability. The question of sustainability of micro-credit among agricultural based households would definitely need state intervention to provide a conducive road infrastructure and markets for products to ensure ability to sell produce at profitable prices in order to commit to loan repayments

3.3 Effects of MFI Credit on Performance via Purchased Factor Use

This section presents results of the switching regression model, which show effects of MFI-credit on total annual farm income through purchased factors. The switching regression model results are preceded by probit maximum likelihood estimates presented in Tables 1. The role of probit regression is to obtain estimates of the selection terms. It also yields results on the factors hypothesized to influence participation in the MFI credit market and used as a first stage for both second stage switching regression model and propensity score matching approaches explained earlier.

The model fit show Wald X^2 of 99.86 for MFI-participants' function and 121.250 for non-participants, both of which indicate 1% significance, implying that the explanatory variables included were important in predicting changes in the dependent. Besides, the inverse mills ratios (selection variables) for both functions show 5% significance, implying existing correlation between error terms of respective first stage and second stage equations, and thus the appropriateness in use of the sample selection correction. The likelihood ratio test of no selection problem was also significant at 1% level for MFI-participants, thus rejecting the null hypothesis of no selection problem.

Results on the explanatory variables show that value of livestock assets and extension contact had different implications between MFI participants and non-participants. For participants, livestock assets had positive influence on the production function as expected, but negative for non-participants, while the reverse applied for extension contact. However, all other traditional variables such as farm size, improved inputs, labour and market access, had similar signs for MFI-participants and non-participants as expected.

On the respective influence of hypothesized variables on production functions, results show that farm size, fertilizer, livestock feeds and planting materials, business income and family labour were more important among MFI-participants. On the contrary, investment in chemicals, hired labour and transfer income were more important among non-participants compared to participants.

Table 3: Heckman (MLE) on Factors Influencing Productive Performance

Full Sample	n=401	n=401
Uncensored Sample	180	221
Wald X^2	99.860***	121.250***
Dep: ln Value of output (Ksh)	MFI-Participants	Non-Participants.
ln of farm size	0.303***	0.258***
ln value of fertilizer	0. 123***	0. 033**
ln value of feeds/plant materials	0.043**	0.011**
ln value of chemicals & vet	0.004**	0.047***
ln of business income	0.084***	0.062***
ln hired labour in hours	0.002*	0.056*
ln family labour in hours	0.308***	0.192**
ln value of livestock assets	0.018	-0.013
ln of age of head	-0.450	-0.172
ln of education of head (years)	-0.310***	-0.016**
ln value of transfer income	0.024**	0.032**
ln number of extension contacts	-0.041	0.095
ln distance to local market in km	-0.083	-0.074
AEZ (1,0)	0.432	0.044
Intercept	12.131	8.953
Inverse mills Ratio	-0.664***	0.161**
Sigma	0.984	0.947
LR X^2 Test for indep. of equations	-16.96***	0.93
Chow F-Value	32.013***	

*=significant at 0.10, **=significant at 0.05 and ***=significant at 0.01

3.4 Factors that Influence Household Poverty

Results on poverty reduction presented using logistic odds ratios and not probability estimates. Odds ratio signifies change in the likelihood of poverty given a unit change in the respective covariates (Ngigi, 2002; Kohler and Kreuler, 2005; Johnston and DiNardo, 2007). Because of ease and meaningful interpretation this study used odds ratio. Poverty is defined here as living below 1 US$ per day per person in a given household. Therefore, the dependent variable was a dummy with (1) indicating that the average per person income in a household fell below 1 US$ per day, and (0), otherwise. This imply that factors that had positive influence on the dependent were those that increased chances for a given household to remain poor, while negative factors reduced chances of a household to remain poor.

Model specification show a log likelihood of -349.58 and a Wald-chi-square (X^2) of 58.33, which was significant at 1% level and 13 degrees of freedom (Table 10), indicating that the hypothesized exogenous factors included in the model were important in explaining changes in poverty. Besides, pseudo R^2 of 27% was also above the statistical threshold of 20%, confirming that a large proportion of changes in poverty were attributed to the covariates considered.

The odds ratio for MFI credit averaged 0.066 and was significant at 6%, indicating important role linkage-credit play in reducing poverty. The fungibility nature of this type of credit allows borrowers to meet a variety of needs including consumption expenditures such as medical, school fees, food and social emergencies, besides expenditures on productive inputs. On education the odds ratio of 0.903,was significant at 5% indicating that literacy is instrumental in accessing credit information. Education enables a household to easily conceptualize information and take advantage of available profitable investment opportunities, which improve household wellbeing. Furthermore, educated decision makers are better equipped to compete for off-farm employment, which command higher income. Therefore, access to knowledge gives important impetus to household welfare.

The odds for livestock assets as an indicator for wealth endowment reveal that a unit increase in livestock assets reduced the likelihood of a household living in poverty by 0.511. In Africa livestock assets are widely used in preparation of land such as the case of ox-drawn ploughs, thus reducing expenditures on labour, and enabling timely land preparation, a factor that is associated with high yields and incomes. Findings on effects of access to transfer income on poverty confirms the hypothesis, with results showing that a unit increase in access to transfer earnings reduced the likelihood of a household remaining below poverty line by 0.668. The odds ratio was significant at 4%, pointing at the heavy reliance of households to transfer earnings to escape poverty, particularly among those residing in the low potential areas. Dependence on transfer income becomes even more acute in marginal production areas, forcing rural households to depend on transfer earnings from working relatives. Policy intervention on transfer earning can take the form of tax rebates, whereby tax cuts could be extended to those who regularly send some of their income as transfers to rural relatives.

Table 4 : Factors that Influence Household Poverty

(Dependent variable: poverty (1=households with less than 1 US$/day/person, 0=otherwise)

Odds Ratio-Logit estimates	N	=	600		LR X^2	58.3***
Log likelihood	-349.58			Pseudo	R^2	0.277
Variable	Odds-Ratio	Std. Err.	z-stat	p>|z|	95%	CL
If MFI-participant (1,0)	0.663	0.16	-1.71	0.058	0.414	1.063
If borrowed other credit (1,0)	0.976	0.199	-0.12	0.903	0.654	1.455
Age of head (yrs)	0.996	0.008	-0.46	0.649	0.981	1.012
Education of head (yrs)	0.903	0.021	-4.35	0.000	0.862	0.945
If head is female (1,0)	1.31	0.294	1.2	0.229	0.844	2.035
If head is male (1,0)	0.861	0.211	-0.61	0.541	0.532	1.392
if access to transfer (1,0)	0.668	0.129	-2.09	0.037	0.457	0.975
if own title to land(1,0)	0.813	0.244	-0.69	0.491	0.451	1.465
Hrs on off-farm activity/day (1,0)	0.965	0.078	-0.44	0.659	0.824	1.13
if group member (1,0)	1.011	0.228	0.05	0.961	0.65	1.574
Distance to market (km)	1.005	0.002	2.32	0.02	1.001	1.009
Ownership of Livestock (ksh)	0.511	0.169	-2.03	0.042	0.267	0.977
AEZ (Nak=1, Kaka=0)	0.631	0.134	-2.18	0.03	0.417	0.955

The odds ratio for market access as measured in distance to the local market was positive (1.005), and significant at 2% level, indicating that a unit increase in distance resulted in 1.005 units increase in the likelihood of a household remaining under poverty. This indicates the negative impact of transaction costs in accessing input and product markets. The effect of market access is thus important for better prices and in lowering production costs for the purchased production inputs. Agricultural ecological zone as indicator for the effects of differentials in climatic conditions had odds ratio of 0.631, which was negative but significant at 3% level. The importance of agro-ecology here indicates a strong linkage between poverty and agricultural production. Female-headed households had a higher chance of remaining poor, while households headed by male had a higher chance of getting out of poverty, although the results were insignificant. The effect of gender here echoes the nature of structures of many rural communities in Africa, where poverty takes a female face.

4 CONCLUSION AND POLICY RECOMMENDATIONS

Participation in MFI credit has gains in income that range between 300 to 480 Euros as well as significant effects on output via purchased factors, 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, result point at the fact that the greatest gains on poverty reduction can only be achieved through stimulating an efficient agricultural sector through credit provision, education interventions, promotion of wealth creation, by ensuring that legal rights to property spreads across all gender, and reducing market transaction costs by improving rural access roads.

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