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Family networks and microcredit access in Kenya

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Abstract

For a long time now, social networks have been hailed for lowering otherwise high information and search cost to agents as well as making a principal's market dominance increasingly ample. We therefore use the data from the 2016 FinAccess Household Survey for Kenya to unravel the effects of family networks in increasing the probabilities of members accessing microcredit. Broadly, we seek to verify whether family networks impact loan uptake by members of households and how this effect differ across gender. Employing the limited dependent variable modelling in our analysis, we find that family networks are vital in reducing search and information costs. Active networks increase the probability of accessing credit compared to non-active networks. This effect is more pronounced among women thus been in tandem with literature on determinants of credit access by women.

Keywords: Social Networks, Credit Access.

1. Introduction

1.1. Background

Access to credit is perhaps among the major nexus to alleviating poverty among the poor households in Kenya. Since the early 1990s and after major constitutional changes in the country, there was concerted effort to ensure that the average citizens were able to smoothen consumption. Owing to population growth and a shallow tax base, the government was increasingly facing difficulties in providing social programs without cost sharing. Medical user fees had been introduced by 1989 while cost sharing in higher education was gaining tract (Chuma *et al.*, 2009; Otieno, 2004). At the same time, there was rising unemployment with paradoxical prevalence of high price levels. Even though domestic investment and entrepreneurship was centrally encouraged, households did not have sufficient access to capital financing (Johnson, 2004). As such, there was need to ensure the citizens were able to access credit and alleviate poverty.

Existing credit facilities that were largely multinational banks were at the time not affordable to smallholder farmers and ordinary citizens who largely characterised the Kenyan population. The search and information costs were therefore inevitably high. This notwithstanding, the government's tendency to highly rely on internal borrowing to finance public expenditure had set the cost of credit punitively high for private borrowers (Were, 2001). There was need for not only increased access but also adequate and affordable credit to the citizenry. Since then, there has been an intensified mushrooming of small microcredit institutions in Kenya leveraging on the high demand for credit. The market forces have had dismal success in lowering the costs of credit as households still face high search and information costs.

1.2. Social networks in credit markets

Social networks have been hailed for lowering high search and information costs (Wydick *et al*., 2011; Conley & Udry, 2001). There is a growing literature on the influence of social networks in easing economic markets. Specifically, relationships among and within households are chief in enabling credit access in low income countries (Okten & Osili, 2004). Proponents of highly cohesive societies postulate that decision units are strongly knit together such that information about its environment is almost *costlessly*[1] acquired. Networks increase the chances that a community will smoothen consumption

[1] With no economic costs.

and investment across periods of fluctuating incomes, and cushion themselves from unprecedented expenditure shocks (Okten & Osili, 2004). Additionally, networks can ease the bureaucracy in accessing microcredit which in turn foster the adoption of advanced technologies, improved health outcomes and improved community literacy (Pitt & Khandker, 1998).

Whereas information asymmetry generally characterizes all markets interactions, non-market institutions can be vital in easing information flow. This reduces imperfections in the market thus enabling ample clearance. In low income countries where borrowers face challenges raising collateral and are generally illiterate, market imperfections are even more pronounced (Adams & Fitchett, 1992). However, social networks are strong non-market institutions that implicitly contribute significantly to information dissemination about active credit markets. In low income countries, the effects of networks is stronger than in developed markets as communities in the former present higher symbiotic interdependency than in the latter (Kelley, 1967; Jackson & Smith, 1999). There is not much done on social networks and their role in economic interactions especially in Africa south of Sahara desert.[2] Family networks are an integral part of social capital that are the smallest decision making unit in a given community. Members relate free and learn from each other symbiotically and implicitly. The effects especially in low income countries can be substantial. The focus has not been attempted before in our study area. As the citizens seek further inclusion, evidence on the implications of salient family relations on the probability of accessing financing is timely.

We hypothesis that in most rural and poor urban households in Kenya, the family unit acts as a stronger social capital than other forms of credit groups formed with aims of accessing credit. Further, we assert that there are costs into joining such groups as compared to one being naturally a member of a given family. Broadly speaking, it is straight forward to analyse a household as a social unit where information about credit can be *costlessly* acquired. The need for credit cannot be overemphasized in average Kenyan households. In the national sample included in the FinAccess survey of 2016, up to 90.1 per cent of respondents reported average monthly incomes of less than KES 30,000. Weighting up this statistic to have a nationally representative figure does not substantially change the outlook. Still, about 32 per cent of the incomes reported

[2.] There is now a growing liberation challenge that ”Sub Saharan Africa” is no synonym to ”Africa South of Sahara”, the former being considered socially demeaning and the latter geographically placing. See information to authors in http://www.jpanafrican.org/submission.htm in the sample largely came from agricultural related sources (Central Bank of Kenya, Kenya National Bureau of Statistics & FSD Kenya, 2016).

Kenya being a low income country has had to grapple with mechanising the agricultural sector that has been a lifeline for many households and a major economic engine. Even though the share of agriculture to GDP has been falling since 1995, the sector employs close to 70 percent of the total labour force (Omiti *et al*., 2009). The decline has been attributed to lack of capital resource for investment coupled with stiff competition from developed markets. Local produce hardly gains entry to international markets owing to quality issues. To this end, access to financing especially by smallholder farmers is inevitably important to smoothen both investment and consumption. By 2016, household financial inclusion stood at approximately 75.3 per cent which was a remarkable growth of about 50 per cent in the last decade (Central Bank of Kenya, Kenya National Bureau of Statistics & FSD Kenya, 2016). Mirrored against the population growth over the period, financial exclusion stood at around 17.4 per cent which was more than 50 per cent decrease in the last decade. Despite such growth in inclusion, 33.1 per cent of Kenyans living in the rural areas and 11 per cent of the urban dwellers are still likely to face major shocks in welfare in the event of drought (Central Bank of Kenya, Kenya National Bureau of Statistics & FSD Kenya, 2016). This points to the fact that many Kenyans depend on rain fed agriculture that is hardly sustainable. Irrigation is highly capital intensive and requires high initial costs where water intakes or harvesting is far from the farm (Ngigi, 2002). Households therefore need affordable channels to access credit thus cushioning themselves from welfare loses.

2. Conceptual framework.

Formally, the concept of our analytical desire revolves around the important question of asymmetric information in credit markets and the attributable search costs. We particularly consider determining the implications of family networks in microcredit market transactions. Consider a member of a household with average income who intends to apply for an investment loan, say for subsistence agriculture. The decision to approach and successfully access credit in a particular credit institution depends highly on the information that the applicant holds about loan application processes, repayment periods and duration, required collateral and insurance. Such information may not be freely available. However, family networks can facilitate easy flow of such quality information thus lowering the cost of accessing credit. Literally, should the applicant have a family member with prior credit access experience, the information cost can be relatively lower than their counterparts with no such family ties.

Empirical literature shows that networks do facilitate information flow and thus ease market clearance. Such networks in decentralised units significantly reduce participants search and information cost (Kranton, 1996). The role of quality information is also demonstrated to facilitate fairness in the insurance market (Akerlof, 1970). Furthermore, there has been sufficient literature on labour markets in which networks have been found to be valuable sources of information in job search and matching (Akerlof & Yellen, 1986; Hosios, 1990; Mortensen & Pissarides, 1999; Stiglitz, 1988). We therefore seek to extend the framework to micro credit markets.

We largely agree with past literature that networks are not magic bullets in disseminating valuable market information. Where networks do not provide sufficient incentives in trusting information about alternative credit institutions, there may be little or no effect. We however hypothesize, unlike in (Okten & Osili, 2004), that family networks may have even stronger effects than social networks. (Okten & Osili, 2004) suggests that since a family will at all times be smaller than other community ties, the effects on credit access may be smaller. However, there is no evidence in this regard. To the contrary, we believe that a family unit is a small entity with relatively higher trusting levels than an artificial community or social groups (neighbours, acquaintances and friends) that may depend on short-term interrelations. Family ties are largely more permanent and less artificial.

From the lenders point of view, lending is particularly a risky venture. In rural and poor urban households, defaulting rates are unsurprisingly high owing to constrained enforcement infrastructure. There is therefore need to screen borrowers to determine their probable types. This is undoubtedly a difficult undertaking by lenders in which more often than not remains unachievable. However, it is our view that lenders regard referrals from family members with prior credit worthiness as a signal to new high-quality borrowers. Plainly speaking, should our hypothetical borrower allude to have been referred by a family member who is credit worthy then the probability that they access credit is higher. Therefore, family ties may act as signals of borrower type where credit institutions may use this to discriminate against *bad* borrowers.

3. Methodology

3.1. The empirical approach

Even though individuals in our sample may have accessed credit from different sources, we believe that their success depended on information they may have gathered. From the data, more than half the respondents reported that they depended mostly on their families for advice on credit matters. Our interest therefore was to estimate the family network effect on the probability that one successfully accessed credit.

There are two outcomes in credit access; having successful access to credit or unsuccessful credit access. Being the outcome variable in our analysis, it is straight forward to assume a limited dependent variable estimation. We use a logit model with credit access status as our dependent variable. Here, we care about the latent movement from not having accessed credit to accessing credit owing to the effects of the family networks and other confounding attributes. We define our dependent variable as;

$$Access = \begin{cases} 1: & \textit{Respondent accessed credit} \\ 2: & \textit{Respondent did not access credit} \end{cases} \tag{1}$$

Where "*Access*" is the dummy dependent variable for 1 if the responded had been awarded a loan facility in the last one year and 0 if they had not had any loan facility in that year preceding the survey. To model expression 1, we illustrate a general functional form of the probability model given as;

$$Pr(y_i = 1|X_i) = F(X_i\ \beta) \tag{2}$$

This is equivalent to writing the right hand side of equation 2 as: $= 1 - F(X_i\beta)$ where F is some function that returns values in the [0,1] interval and thus restricts the outcome probabilities from spilling out of the range and also;

$$Pr(y_i = 0|\beta, x_i) = F\left(-\sum x_i\ \beta\right) \tag{3}$$

Formally, a binomial logit function assumes the logistic distribution of the errors. Consider the function F as the standard logistic cumulative distribution function expressed as;

$$1 - F\left(-\sum X_i'\beta\right) = \frac{e^{\sum X_i'\beta}}{1 + e^{\sum X_i'\beta}} \tag{4}$$

So that;

$$F\left(-\sum X_i'\beta\right) = \frac{e^{-\sum X_i'\beta}}{1 + e^{-\sum X_i'\beta}} = \frac{1}{1 + e^{\sum X_i'\beta}} \tag{5}$$

Where X is a vector of model characteristics while the β's are the coefficients in the logit regression.

Since the expectation of the dependent variable conditional on the regressors is nonlinear in nature, the maximum likelihood estimation is suitable. The advantage is that MLE is based on the distribution of y given $\boldsymbol{X}$ and thus the heteroscedasticity in $Var(y|\boldsymbol{X})$ is accounted for. The parameter estimates are obtained by assuming for a moment, a Bernoulli random variable whose probability distribution function is given by;

$$\Theta(y_i) = p_i^{y_i}(1 - p_i)^{1-y_i} \tag{6}$$

Where pi = Pr (y_i = 1). If we assume that the probability model is given by equation 2 and our observations are obtained through simple random sampling from the same underlying data generating process, then the joint probability distribution function of the sample, given the observations $\boldsymbol{X}$ and parameter vector $\boldsymbol{\beta}$ will be given by;

$$\Theta(y_1, \dots, y_n|\boldsymbol{X}_1, \dots, \boldsymbol{X}_n, \boldsymbol{\beta}) = \prod_{i=1}^{n} F(\boldsymbol{X}_i\boldsymbol{\beta})^{y_i}[1 - F(\boldsymbol{X}_i\boldsymbol{\beta})]^{1-y_i} \tag{7}$$

Consequently, we can obtain the log-likelihood function of equation 7 such that we have;

$$\begin{aligned}\ln L\,(\boldsymbol{\beta}|\boldsymbol{X}_1..\boldsymbol{X}_n, y_1..y_n) \\ &= \sum_{i=1}^{n} y_i \, ln\, F(\boldsymbol{X}_i\boldsymbol{\beta}) \\ &+ \sum_{i=1}^{n}(1 - y_i) ln\,[1 - F(\boldsymbol{X}_i\boldsymbol{\beta})]\end{aligned} \tag{8}$$

We maximise this expression with respect to $\boldsymbol{\beta}$. In the case of well-behaved functions F we do this by differentiating with respect to the vector $\boldsymbol{\beta}$ and setting the resulting gradient to zero. In this case:

$$\frac{\partial \ln L}{\partial \beta_j} = \sum_{i=1}^{n} \frac{y_i f(\boldsymbol{X}_i\beta)\boldsymbol{X}_{ij}}{F(\boldsymbol{X}_i\beta)} - \sum_{i=1}^{n} \frac{(1 - y_i) f(\boldsymbol{X}_i\beta)\boldsymbol{X}_{ij}}{1 - F(\boldsymbol{X}_i\beta)} \tag{9}$$

$$= \sum_{i=1}^{n} \frac{f(\boldsymbol{X}_i\beta)\boldsymbol{X}_{ij}(y_i - F(\boldsymbol{X}_i\beta))}{F(\boldsymbol{X}_i\beta)[1 - F(\boldsymbol{X}_i\beta)]} \tag{10}$$

So that the first order conditions for an optimum are given by the k equations

$$\sum_{i=1}^{n} \frac{y_i - F(\boldsymbol{X}_i\hat{\beta})}{F(\boldsymbol{X}_i\hat{\beta})[1 - F(\boldsymbol{X}_i\hat{\beta})]} f(\boldsymbol{X}_i\hat{\beta})\boldsymbol{X}_{ij} = 0, \qquad j = 1, \dots, k \tag{11}$$

In the case of a logit model, the first order conditions in equation 11 take the simple form;

$$\sum_{i=1}^{n} \left(y_i - F(\boldsymbol{X}_i\hat{\beta})\right) x_{ij} = 0, \tag{12}$$

as $f(z) = F(z)\,[1 - F(z)]$. This equation is mirrors the first order conditions for the linear regression model. Note that $F(X_i\, \beta) = p_i$ and this is an estimate of $E(y_i \mid \boldsymbol{X}_i)$. Consequently $y_i - F(\boldsymbol{X}_i\, \beta) = \mu_i$ is the *residual* in this relationship. Our estimates $\boldsymbol{\beta}$ therefore ensure that these residuals are orthogonal to the $\boldsymbol{X}$ values. One implication of this is that in models which have an intercept, the mean of the predicted probabilities will be equal to the sample proportion. This follows since if $x_{i1} = 1$ for every i, then;

$$\sum_{i=1}^{n} (y_i - \hat{p}_i) = 0 \tag{13}$$

Generally these equations do not have closed form solutions. The solutions are obtained by numerical methods. In the case of the logit and probit model the log likelihoods are globally concave and the search algorithm converges quickly on the solution (Wooldridge, 2012).

For our analysis, we assume a simple functional relationship given as:

$$y_i = \gamma_0 + \sum X_i\beta + \varepsilon \tag{14}$$

Where X is a vector of all regressors including our network variables of interest. The dependent variable y is the observable credit access outcome in which $y = 1(y^* > 0)$ represents the indicator function.

3.2. The Data

The study used cross-sectional data from the Kenya FinAccess household survey of 2016. The Kenya FinAccess household survey program measures access to and demand for financial services among adults in a nationally representative survey. The sample is nationally representative and based on the fifth National Sample Survey and Evaluation Program (NASSEP V) household sampling frame of the Kenya National Bureau of Statistics (KNBS). The total sampled respondents included 8,665 individuals.

At least for our dependent variable, there were no missing responses. There were about 57.33 per cent of the respondents who had taken up credit from a lender within the period of one year preceding the survey. Majority of these loans were from micro-credit institutions. Further we assume that the *loanees* made decisions to access credit having sourced for and accessed information regarding possible lenders, requirements and obligations for loans. Approximately 41.08% of individuals in the sample depended highly on their immediate family ties for financial advice. This advice largely include possible sources of credit and obligations hitherto. Others wanted moral persuasion on whether it was agreeable to use family property as collateral. We treat this globally as information relevant to accessing credit as members would not agree had they been in doubt about financial institutions.

Total household monthly income was captured as a sum total of all income generating sources that a household had in a given month. This involves an absolute estimate of contributions to the household income basket by each member plus other entity related incomes. There is an inherent problem with recall bias where many of low income households do not recall incomes accurately more so when aggregately asked. Responses to such income questions in survey data lead to potential rounding off around definite figures. This renders the normality assumption in the distribution of income rather indefensible.[3] There were very few (129 out of the possible 8665) with zero incomes. We however used the log form of this variable.[4]

Other than family networks, there are other conceivable networks that can be avenues to information source (Kelley, 1967). In our data applicants reported to have sourced information from other sources. We grouped these sources to form three more networks through which information about successful credit access could be achieved. These include media networks, financial institutions themselves and individual based evaluation. In the last of these networks, there were almost 43.31 percent of respondents who reported to have depended on their own evaluation about credit requirements. Approximately 41.08 percent depended on family members, 10.16 percent on financial institutions while only 1.96 percent depended on advertisements on media.

3. It is evident from our data that households rounded off responses they gave for income estimates. We plot data points on the income variable in a scatter plot restricting to several random thresholds. We find huge spikes around definite intervals and figures. The analysis is available on request from the corresponding author as well as Stata do files for replication.

The quality of the network is vital in whether it leads to successful credit access (Wydick *et al*., 2011). It is irrefutable that some information about credit access could be spontaneous rather than quality. At the same time, measuring the quality of a network may not be straight forward. In our case, we proxy quality of networks by the number of economically active members recorded in a household. These were captured as members who had active bank accounts in mainstream banking. The hypothesis is that they by large understand the financial institutions better and would be in a position to offer quality information about financial services. Finally, we include other demographics such as the respondent's age, its quadratic, highest level of education, marital status, religion and gender.

4. Results

We present our main results in two analytical tables. Firstly, we assume at baseline, two simple regressions of networks on credit access. The first specification in table one reports the estimate of a simple regression of family networks on access to credit. The second specification considers all possible network channels in our data through which information could be sourced.

From specification 1 we find a negative relationship between family networks and access to credit even though it is straight forward to note that the specification is biased. We are however interested in whether family networks are in themselves significant predictors of access to credit. In adding other possible networks, our coefficient of interest remains statistically significant but significantly changes the sign to positive. The average partial effects increase by more than one hundred percentage points. Additionally all networks are significant predictors of access to credit. With these baseline results, we proceeded to add more controls in our estimations while observing the behaviour of our coefficient of interest.

TABLE 1: RELATIONSHIP BETWEEN NETWORKS AND CREDIT ACCESS

	Specification 1		Specification 2	
VARIABLES	Logit 1	APE	Logit 2	APE
Depends on family networks	-0.279*** (0.0519)	-0.0504*** (0.00921)	0.354** (0.163)	0.0636** (0.0294)
Depends on self-evaluation			0.442*** (0.162)	0.0793*** (0.0290)
Depends on financial institutions			1.438*** (0.171)	0.318*** (0.0403)
Depends on media adverts			0.762*** (0.231)	0.158*** (0.0534)
Observations	8,665	8,665	8,665	8,665

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1
Specification 1 is a simple regression of family networks on credit access status with no other controlling covariates. In specification 2, we control for three more forms of information sources identified as network. Estimates under the columns labelled APE are the corresponding average partial effects after the logit estimation.

Table 2 presents three more specifications that we considered. For obvious reasons, we are only interested in the signs of the coefficients in the logit regression. We then interpret the marginal effects of the key variables of interest. Having controlled for the possible confounding factors, we find significant effects of family networks on the probability that an individual accessed credit in all specifications. For instance, from specification 3 we find that applicants depending on family networks had 6.6 percentage points higher chance of accessing credit than their counterparts in the sample. We use the categorical education variable in specification 3. Inclusion of the categorical variable weakens the confidence in which family networks predict probabilities of credit access. We drop the categorical education variable in specification 4. The average partial effect is largely statistically significant and goes up to approximately 8.5 percentage points. In the last of the estimations, we used the continuous variable on education measured as years of education spent by a given respondent. This approach is in many cases flawed as an extra year in school may not entirely imply that an individual moved to a higher level of schooling. In rural Kenya, there are substantial cases of people repeating a grade year. Where this may be significant for our sample, the interpretation of the years of education coefficient may not be straight forward. We however, for robustness consideration include the years of education in specification 5. Other than the magnitude of the coefficient of the average partial effects, we do not find contrary results. There is 7.2 percentage point increase in probability that a respondent will access credit had they depended on family networks. We find it compelling to test the robustness of our results using the education variable owing to the findings of Mwangi and Sichei, (2011) that postulates that the relationship of education level and credit is not directly established. In fact, education is potentially endogenous especially in poor household. Additionally, the bulk of respondents in our sample are more likely to borrow to finance education of their family members. Therefore, it remains an empirical question whether higher education leads to higher chances of accessing credit, or successful credit access leads to increased years of schooling. In our case, hypothesising that education can promote easier processing of credit information and hence increasing chances of credit access does not significantly change the estimated influence of family networks even when we drop the education covariate.

Our results are similar to Wydick *et al*., (2011) who calculates an elasticity of social imitation (ESI) indicating that if the proportion of people accessing microfinance in a church network doubles, the probability of an individual household accessing microfinance increases by 14.1%. This magnitude is similar to estimates of further calculated ESIs considering televisions and cell phones within church and neighbourhood networks. The study concludes that information pertaining to credit access becomes cheaply accessible and thus raising the probability that an individual in the group accesses credit. Other studies including Kranton, (1996), Akerlof, (1970), Okten & Osili, (2004) and Adams & Fitchett, (1992) arrive at similar conclusions thus consolidating the pivotal role played by networks in costless information dissemination.

Female respondents benefit more from active family networks. Okten & Osili, (2004) and Mwangi and Sichei, (2011) allude that indeed, women successfully seek microcredit more often than men. In all our specifications women have significantly higher chance of successfully accessing credit than the male counterparts. At the same time women generally seek information before committing to financial obligations. The most salient argument supporting this behavioural preference pegs on the social standing of women in most households in Africa south of Sahara. This cultural setting may in our case work to the advantage of female respondents in that in the advent of seeking for permission from household heads, they acquire valuable information concerning requirements and expectations of credit access.

Table 2: More Estimation Results (various specification)

	Specification 3		Specification 4		Specification 5	
VARIABLES	Logit 3	APE	Logit 4	APE	Logit 5	APE
Depends on family networks	0.498* (0.269)	0.0663* (0.0361)	0.618** (0.258)	0.0851** (0.0360)	0.535** (0.263)	0.0721** (0.0359)
Depends on self-evaluation	0.524** (0.267)	0.0694* (0.0355)	0.620** (0.256)	0.0840** (0.0348)	0.557** (0.261)	0.0744** (0.0350)
Depends on financial institutions	1.337*** (0.288)	0.223*** (0.0554)	1.463*** (0.278)	0.257*** (0.0562)	1.354*** (0.283)	0.231*** (0.0558)
Depends on media adverts	0.643* (0.376)	0.0973 (0.0638)	0.896** (0.364)	0.147** (0.0688)	0.711* (0.372)	0.110* (0.0655)
Currently divorced	0.400** (0.199)	0.0454* (0.0235)	0.354* (0.195)	0.0429* (0.0244)	0.502** (0.200)	0.0573** (0.0240)
Widowed	0.395** (0.185)	0.0447** (0.0213)	0.157 (0.180)	0.0179 (0.0207)	0.394** (0.187)	0.0436** (0.0209)
Currently married	0.643*** (0.129)	0.0783*** (0.0141)	0.524*** (0.125)	0.0667*** (0.0145)	0.708*** (0.132)	0.0861*** (0.0141)
Female (1 = Yes)	0.598*** (0.0886)	0.0749*** (0.0104)	0.511*** (0.0876)	0.0658*** (0.0106)	0.567*** (0.0884)	0.0717*** (0.0105)
Age	0.110*** (0.0139)	0.0145*** (0.00180)	0.114*** (0.0141)	0.0154*** (0.00187)	0.115*** (0.0141)	0.0153*** (0.00184)
Age squared	-0.000996*** (0.000152)	-0.000131*** (1.97e-05)	-0.00112*** (0.000154)	-0.000151*** (2.05e-05)	-0.00108*** (0.000154)	-0.000143*** (2.02e-05)
Has attended primary school	1.197*** (0.136)	0.125*** (0.0115)	No No	No No	No No	No No
Has attended secondary school	1.387*** (0.154)	0.155*** (0.0160)	No No	No No	No No	No No
Has attended technical college	1.887*** (0.265)	0.243*** (0.0451)	No No	No No	No No	No No

Has attended university education	0.303 (0.719)	0.0230 (0.0605)	No No	No No	No No	No No
Years of Education	No No	No No	No No	No No	0.461*** (0.0554)	0.0612*** (0.00724)
Log of total household income	0.230*** (0.0344)	0.0303*** (0.00449)	0.260*** (0.0343)	0.0351*** (0.00459)	0.225*** (0.0343)	0.0298*** (0.00452)
Islam	-0.814*** (0.152)	-0.0915*** (0.0141)	-1.386*** (0.141)	-0.142*** (0.0101)	-1.077*** (0.146)	-0.116*** (0.0120)
Other religions other than Islam and Christianity	-0.240 (0.264)	-0.0316 (0.0327)	-0.506** (0.257)	-0.0672** (0.0296)	-0.312 (0.264)	-0.0418 (0.0325)
Network quality (Family member has bank account)	0.0967 (0.0948)	0.0129 (0.0128)	0.221** (0.0925)	0.0308** (0.0133)	0.0872 (0.0953)	0.0117 (0.0130)
Observations	5,597	5,597	5,597	5,597	5,597	5,597

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1
"No" implies that the specification did not include the corresponding variable. We used both the education variables in our estimations.
One captured the highest level of education attained by an individual which we used in specification 3. We noted that by including education by categories, our family networks coefficient weakly predicted the probability of accessing credit. In specification 4 we exclude the levels of education in the estimation. Specification 5 uses the years of education spent in school and reported by the respondents as opposed to the highest level they had attained.

We find a nonlinear relationship between an applicant's age and access to credit in all specifications. The turning points are estimated at approximately 55, 51 and 53.5 years in specifications 3, 4, and 5 respectively. In our conception, we believe that on average, most individuals at this age are sufficiently knowledgeable of the world of credit access and thus any further information dismally influences their credit access chances. Again, most of the individuals at this age are viewed as high credit risk by lenders owing to their advanced age and diminished collateral assets as they approach their retirement and economically unproductive ages. However much information they may hold on credit access avenues, adverse selection in credit markets may arguably play higher influence. Additionally, for most of our sample, respondents at this age are highly likely to depend on their children for any financial needs as opposed to seeking credit. Other than the respondents with University level education, each of the other categories indicated a significant increase in probability of accessing credit. Even though a weak empirical overlook, University graduates are more likely to seek credit from mainstream banking systems as opposed to microcredit institutions. Most graduates would hypothetically stand a fairer chance to access formal employment which in turn formalises their avenues to most admissible collateral requirements in mainstream banking. Additionally, majority of microfinance institutions target the unbanked population and small business entities. Indeed, a closer look into our data revealed significantly low numbers of degree graduates seeking credit from microcredit institutions. Nonetheless, from specification 5, an extra year of education raises the probability of accessing credit by 6.1 percentage points. Conforming to this analogy, being Muslim significantly reduces chances that one will access credit compared to been Christian despite the form of networks one subscribes to. This finding further conforms to our limited understanding of the relationship between Islam and credit seeking. It is quite unlikely that Muslims would seek credit from secular financial systems (Ali and Khwaja, 2012).

High income seem to benefit more in accessing credit than low income households. Across all specifications, total household income remains a strong predictor of credit access. It is conceivable that higher incomes signal more financially literate respondents whose networks are more active than low income earners. Specifically, a unit increase in the log of household income implies an approximate 3 percentage point increase in the probability of accessing credit. As we cited earlier, we cannot at least with the data available, guarantee the veracity of the income variable. There were potential confounds in answering the income question and there could be cases where respondents summed up resources advanced to them as credit together with their monthly incomes. The caveat would therefore be that this result would only be valid to the extent that the survey captured the true income value.

Unlike Okten & Osili, (2004) who find that family networks are insignificant in credit information dissemination, our results have shown that using binary choice models, family networks are significant channels of information dissemination. Okten & Osili, (2004) argue that due to the relatively smaller size of the family unit, there is hardly no information about credit sources passed. However, in a more nationally representative sample as the FinAccess, approximately 41 percent of respondents reported to have depended on family members for information. The argument on size of a family unit being small also seems flawed in that, rather what should be at stake would be how much one trusts the source and the quality of information as opposed to the number of people they seek information from. In other words, advice on successful credit access can come from a single quality source and still be largely influential than being from many less quality sources and thus less helpful. Even though we cannot defend our assertion using data analysed in this paper, Okten & Osili, (2004)'s second claim that incomes are largely correlated within family networks may not be generalizable from a practical point of view. Thomas (1990) finds vast intra-household resource allocation differentials and that even where resources would be equal for husband and wife, demand for household needs by the two household members is vastly different. Anderson and Baland, (2002) postulate that in informal settlements in Kenya, women are on average more resource endowed than their male counterparts. Even more, they feel compelled to join rotating saving and credit associations (roscas) as a form of safeguarding their resources from immediate consumption use by their spouses. Therefore, incomes can be vastly diverse within a family network and it would then be interesting to see whether networks mediate the need to increase welfare of members. We would need individual income data to support an assertion that in our sample, intra-household incomes were rather vastly diverse than closely related.

5. Conclusion

We have endeavoured to depict the effects of family networks on credit access. Our hypothesis has been that networks offset search costs. Networks also ameliorate complex market information asymmetries and reinforce inclusion. That is to mean that networks enhance avenues through which market failure is reduced. Clearly, borrowers with active networks have a higher chance on average in accessing credit. Exposing the possible avenues through which information can be "costlessly" channelled, increases efficiency in which lenders can capitalise on. Lenders can give incentives to borrowers by encouraging them to pass information to their family members about credit access. Unlike the peer-borrowing-groups that most microfinance institutions depend on in lending, families based networks would be the best co-insurance mechanisms in addition to lowering search and information costs on borrowers. Peer-borrowing-groups are also one of the largest loan defaulters in Kenya.

Even though silently, the analysis in this paper re-emphasizes the need to have all possible means of increasing credit access in Kenya. This is an inevitable challenge for the desired country goals and the vision 2030. Further research should expand this study, in the availability of data, to compare credit access in both mainstream banking and the microcredit sectors and whether family networks have varied effects. A panel study is also to be considered to unravel the dynamic nature of the network effects over time.

Additionally, there should be further research that focuses on determining the reverse case of family networks. As we earlier suggested, strong social and family ties may as well have negative effects in accessing credit. This can be more pronounced where a member of a family uses the credit resources to cloud-out family level needs. This way, there may be no reason for other members of the family to seek credit.

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