Risk Behaviour and Group Formation in Microcredit Groups in Eritrea

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SOM-theme E: Financial markets and institutions

Abstract:

We conducted a survey in 2001 among members and group leaders of borrowers who accessed loans from two microcredit programs in Eritrea. Using the results from this survey, this paper aims to provide new insights into the empirical relevance of the homogeneous matching hypothesis for microcredit groups in Eritrea. Since the methodology to test for homogeneous matching needs estimating risk behaviour, the paper also provides new evidence on risk behaviour of members of microcredit groups in Eritrea. Our main results strongly indicate that groups are formed heterogeneously. Most importantly, we do not find support for the matching frictions hypothesis, in the sense that even if we control for matching frictions, credit groups in Eritrea do not seem to consist of borrowers of the similar risk type.

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1. **Introduction**

The performance of microfinance institutions has been debated quite extensively in the literature (for a recent survey, see Morduch 1999). This debate has focused on the (unconventional) methods that microfinance institutions use to improve borrowers' payback behaviour. The theoretical literature has especially dealt with the implications of group lending practices with jointly liable borrowers (see *e.g.* Ghatak and Guinnane, 1999).[1] A joint liability contract specifies that the entire group is liable for loans that are given to individual group members. A well-known example is the Grameen Bank's group lending program. It has been emphasised that group lending with joint liability may lead to *peer-monitoring or peer-pressure* among group members which reduces problems of *moral hazard* and *enforcement* (Stiglitz, 1990 and Besley and Coate, 1995). A reason is that a high joint liability component in the debt contract provides incentives to borrowers to choose a safe investment project.

A recent group of theoretical papers has emphasised that joint liability induces group members to self-select each other (*e.g.* Ghatak, 2000). These papers argue that the optimal outcome is one in which all borrowers with the same probability of success match together (homogeneous matching). It has also been argued that the optimality of homogeneous matching only holds in a frictionless world (Sadoulet and Carpenter, 2001 and references therein). However, the real world is characterised by frictions due to *e.g.* imperfect information, the unavailability of partners with the same risk characteristics, the inability to enforce contracts and the inability to fully screen and monitor group members. The advocates of the matching frictions theory argue that heterogeneous matching might take place, but that the heterogeneity is entirely due to so-called "matching frictions." In other words, the matching frictions theory suggests that there will be homogeneous matching in the case where the analysis controls for matching frictions. In other words, when there are matching frictions leading to some heterogeneity, the matching is still "essentially homogeneous"; heterogeneity is simply due to frictions and therefore generates deviations from optimality. Yet, empirical evidence on the homogeneous matching hypothesis in general and the matching frictions theory in particular is lacking. One of the few exceptions is Sadoulet and Carpenter (2001) for microcredit groups in Guatemala.

This paper takes up the challenge by aiming to examine the empirical relevance of the homogeneous matching hypothesis for microcredit groups in Eritrea. We conducted a survey (personal interviews) in 2001 among members and group leaders of borrowers who accessed loans from two microcredit programmes in Eritrea.[2] The survey includes questions related to the group formation process, and provides information that can be used to test the matching frictions hypothesis.

The paper is organized as follows. Section 2 provides some information on microcredit groups in Eritrea. Section 3 surveys the group formation and homogeneous matching literature that is most closely related to our paper. In Section 4 we explain the methodology we use to test the matching frictions hypothesis. In Section 5 we explain how we measure risk, a variable that we need to test for homogeneous matching. Section 6 presents two groups of independent variables that are assumed to affect risk behavior. In this section we also apply factor analysis to regroup these variables in a smaller number of factors. In Section 7, we estimate risk behavior. The results of this equation are used in Section 8 to test whether homogeneous matching holds if matching frictions are accounted for. Finally, Section 9 concludes.

2 Organisational profile of the group lending programs in Eritrea.

In Eritrea there are two microfinance institutions. The first is the Saving and Credit Programme (*SCP*), which operates as a component of the Eritrean community development fund (*ECDF*) since July 1996. The other is the Southern Zone Saving and Credit Scheme (*SZSCS*) that has been launched by the Agency for Co-operation and Research in Development (*ACORD*) in 1994.

The saving and credit program ECDF/SCP

The government of Eritrea, the World Bank (IDA) and loans and grants from donors are the main sources of funds for ECDF/SCP. The aim of the SCP is to provide financial services to the vulnerable group in the rural and urban areas who have no access to formal banking services. Grassroots-based solidarity groups owning and operating “Village Banks” will form the backbone of the program.

While its immediate objective is to provide access to credit and saving to people who are outside the orbit of the formal banking network, its long term objective is to strengthen its institutional setting and together with SZSCS, establish the legal, regulatory and judicial framework for the microfinance sector of Eritrea.

The SCP is principally based on the creation of autonomously functioning Village Banks, “VB,” typically serving 35-105 members. The village bank is administered at the village level through a saving and credit unit made up of three members. The village/ area administrator acts as a chairperson while the other two from client members are responsible for accounts and record keeping. All loan applications are processed in the village bank before they are forwarded to the regional SCP credit officer for final decisions and payments. However, repeated loans are processed during VB monthly meetings and loans are granted on the spot. Borrowers are allowed to select loan maturity periods instead of requiring that all borrowers comply with the fixed loan terms. Loans range from 1000 to 10000 Nakfas, although individuals are allowed to withdraw less if they want to. Note that Nafka is the name of the Eritrean Currency. The official exchange rate is US$ 1 = 14 Nakfas.

SCP charges a 16% interest rate, which is higher than what the commercial banks in Eritrea charge.

Beneficiaries will be eligible for SCP credit if and only if they are members of a solidarity group (SG). The solidarity group should consist of 3-7 members. The SG has to be governed by the principles of joint liability and members should not belong to the same family. Group members become eligible for loans only after having successfully accumulated 10 % mandatory savings within a period of three months.

The Southern Zone Saving and Credit Scheme (SZSCS)

The main objective of the Scheme is to provide underprivileged people access to credit. In addition it has the objective of strengthening the institutional capacity of the scheme.

The foundation of the scheme consists of 5-7 member credit and saving groups (CSGs) who are established based on the joint liability principles. The credit and saving groups elect five members to a Village Credit and Savings Committee (CSC). Loan applications forwarded by borrowing groups are screened and approved by the CSC. Once approved by the CSC the credit officer will forward the loan after further evaluation to the borrowing group in one of the monthly group meetings. Saving is mandatory and groups have to save 5 % of the requested loan amount before requesting a loan. Loans range between Nakfa 100 and 8000 and the maturity period is determined based on a mutual understanding between the loan officer and the borrower. The scheme charges an interest rate of 14 %.

3. Other literature on group formation and homogeneous matching

Most of the matching literature draws heavily from the work of Becker (1993), who has worked extensively on marriage matching theory. Ghatak (1999) presents a simple model why self-selection of groups will lead to homogeneous matching. Here we explain the main insights.

The main reason why the theoretical literature argues that borrowers with equal risk profiles will form groups is that the value of having a safe partner is positive for all individuals and increasing in the own probability of success. This implies that the gain for a risky borrower of joining a group with a safe borrower is always lower than the loss for a safe borrower of forming a group with a risky borrower. Hence, a risky borrower can not cross-subsidise a safe borrower in order to be accepted as a partner, leading to groups containing partners of equal risk.

One of the most sophisticated theoretical models on the homogeneous matching hypothesis is due to Ghatak (2000). He shows that if lenders are able to offer a continuum of debt contracts, containing different values for the interest rate and the joint liability component, incentive compatible separating equilibria may result. The safe types prefer a combination of a high joint liability component and a low lending rate, whereas the opposite will hold for a risky borrower. In this way, a lender may obtain information on the type of the borrower.

Xinhau Gu (2000) also deals with the formation of borrowing groups through the exploitation of local information and joint liability. He states that static models implicitly assume a borrower to always be endowed with acceptable (capable) projects. However, entrepreneurs usually have difficulties finding investment opportunities and dynamic search models are useful tools to address such problems. He examines the impact of uncertainty about investment opportunities on borrowers' project search decision and on the rate of loan repayment. He shows that safe borrowers prefer to group with safe borrowers since the effective cost of borrowing is positively related to risk taking by group members.

Laffont (2000) shows the role of group lending in differentiating between borrowers of different types (adverse selection). He states that group-lending contracts offer a subtle method of discrimination between borrowers. When collusion between borrowers under complete information is allowed for, group lending as an instrument improves discrimination between entrepreneurs of different types. So, similar types match together.

Sadoulet (1999) presents a model that challenges the commonly assumed homogeneous matching hypothesis. In his model, group membership is endogenous and group performance depends on both members' types and on the distribution of those types. According to Sadoulet, group members choose partners in a context of missing insurance markets. The point he wants to make is that if insurance markets are missing, then homogeneity is not optimal anymore. Heterogeneity emerges as a constrained first best choice. Sadoulet suggests that members set up insurance arrangements within their group in which partners will cover each other's loans in case of project failure. The reason for insurance is that borrowers live and work in risky environments and hence need insurance. If a member, who is able to insure a partner in need, refuses to pay for him, he will lose together with other member's access to future loans from the program because of the joint liability principle. Alongside these insurance arrangements there exists transfer payments between members when both members are successful to remunerate the safe one for covering for the risky one in times of need. Thus, this insurance arrangement is taken to be an important part of the group formation process. To this end, Sadoulet's model suggests a non-monotonic matching pattern in which safer borrowers will always form groups heterogeneously with partners riskier than themselves. Middle-type borrowers match either heterogeneously with safer borrowers or homogeneously with borrowers of their type depending on whether these are available. Finally, the riskier borrowers match homogeneously. Note that the models by Ghatak (1999) and Sadoulet (1999) are similar. Ghatak gets homogeneous matching since his model is static, whereas Sadoulet gets heterogeneous matching since his model is repeated. Moreover, in the model by Ghatak, the benefit of homogeneous matching is that it improves repayment rates and thus leads to lower interest rates. The problem is that the decrease in the interest rate can not compensate the safe borrowers for having to cover the risky borrowers' loans when they fail. So, safe and risky borrowers will not form groups. In the model by Sadoulet the benefit is not lower interest rates, but access to future loans, which has a much bigger direct value.

Armendariz de Aghion and Gollier (2000) state that, in urban economies with heterogeneous, anonymous, and relatively mobile borrowers, random (rather than assortative) matching is incentive compatible for all types of borrowers. A particular feature of their paper is that they assume that borrowers do not know each other. They show that cross-subsidisation among members provides a kind of a collateral that reduces the negative externalities from risky to safe borrowers. The main implication of their work is that, as we move away from village economies by allowing imperfect information, assortative matching no longer leads to an equilibrium, and yet group lending can improve efficiency and enhance welfare.

There are few empirical studies available that have rigorously tested the homogeneous matching hypothesis. Most empirical studies have simply assumed that homogeneous matching takes place. Some studies, however, provide some insights. For instance, Van Tassel (2000), for groups belonging to BancoSol, Bolivia, found that groups match heterogeneously in unobservable business characteristics.

The only empirical paper available that has rigorously tried to investigate the matching of group members is the one by Sadoulet and Carpenter (2001). For credit groups in Guatemala they estimated the relationship between risk and the level of risk heterogeneity in the individual groups, explicitly accounting for the endogeneity of group formation and of borrowers' choice of project risk. Their results show that borrowers in Guatamala group heterogeneously, and that the heterogeneity cannot be explained by matching frictions. In line with the theoretical paper by Sadoulet (1999), they suggest that borrowers might want to form heterogeneous groups in order to set up insurance arrangements.

4. The methodology: The role of matching frictions

We follow the methodology set out by Sadoulet and Carpenter (2001). The reader is referred to their paper for a detailed explanation of the methodology. The main problem we have to deal with is as follows. The matching frictions theory states that homogeneous matching only holds in a frictionless world, and that all heterogeneity comes from matching frictions. This implies that there should be no statistically significant relationship between first best risk (risk in a frictionless world) and heterogeneity. In order to test this theory, we need indicators for first-best risk and matching frictions. The problem is that these variables are not observable. Sadoulet and Carpenter (2001) solve this problem as follows. They start by arguing that with matching frictions the full system of equations (the structural model) can be specified as:

1) $h_i = H(r_i^*, f_i)$

2) $r_i = R(X_i, f_i)$

3) $r_i^* = k(X_i, 0)$

where h_i is a measure for risk heterogeneity within a group for group member i, r_i is actual risk of group member i, r_i^* a borrower's choice of risk in a frictionless world, f_i are matching frictions (in fact it refers to a matrix of variables determining the friction level f_i) and X is a set of variables that determines the risk choice in a frictionless world (r_i^*). If the matching frictions hypothesis holds, $\frac{\partial h_i}{\partial r_i^*} = 0$.

The trick is to first estimate the actual risk equation, for which we take, for reasons of convenience, a linear specification:

4) $r_i = X_i\alpha + f_i\beta + \varepsilon_i$.

From this regression, estimated values for first-best risk and matching frictions can be obtained:

5) $\overline{r_i^*} = X_i\overline{\alpha}$

6) $\overline{\beta f_i} = f_i\overline{\beta}$

These estimated values are then substituted in the equation for heterogeneity:

7) $h_i = \alpha + \gamma\overline{r}_i^* + \delta\overline{\beta f}_i + \varepsilon_i$

Homogeneous matching will be empirically confirmed if $\gamma = 0$. It is expected that δ≥0.

5. How to measure risk?

The first step in the analysis is to develop a measure for risk, which is needed to estimate the risk equation (equation 4). Note that in the theoretical models it is assumed that there is only one project available per individual, which implies that projects and borrowers are interchangeable. This also implies that the theoretical measure for risk refers to both the riskiness of the borrower and the project. However, empirically there is no perfect measure for this theoretical risk concept available. We proxy the theoretical concept of risk by developing a measure for the risk of a borrower's repayment strategy. Even this is not directly measurable, and therefore has to be proxied by an (admittedly imperfect) indicator. In line with Sadoulet and Carpenter (2001), we proxy risk (r) by:

$$r_i = \frac{P_i - S_i}{P_i} \text{, for } P_i \geq S_i \text{ .}$$

and $r_i = 0$ for $P_i < S$

where P_i is the loan payment due per month (loan payments are once per month for the credit programmes)[3] and S_i is the amount the borrower reported having saved one weak before the due date to cover the loan payments.[4] The risk indicator varies between 0 and 1. The higher the percentage amount saved a week before the repayment date, the lower is the risk of a borrower's repayment strategy. It should be noticed that a possible caveat of our risk measure is that a person who gets a fixed payment (more than P_i) in the week before the payment can be very safe despite the fact that $S_i=0$. However, we don't think that this will substantially affect our results since this does not seem to happen often in practice. Table 1 gives information on the risk measure, and the variables used to construct this measure. The table also provides data on the credit amount. Figure 1 gives a kernel distribution of r.

<insert Table 1 and Figure 1 about here>

The value of loans ranges from 750 Nakfas to 8500 Nakfas, with mean and median loan size of 3961 and 3500 Nakfas. Loan terms vary between 3 months and 24 months. Loans are used most of the time for working capital (information not in table). The mean of our risk indicator is about 0.17, with an even lower median (0.09). Of the 351 borrowers, 105 are left censored on the risk measure (r=0), 10 are right censored (r=1) and 236 are uncensored (0<r<1). Note that none of the variables is normally distributed.

6. Variables proxying for first-best risk and matching frictions

The next step in the analysis is to determine which variables possibly affect risk, which of those variables are related to first-best risk and which of them are related to matching frictions. Hence, referring to equation 4 above, we need to determine a vector of variables X (first best) and f (matching frictions).

Matching frictions (f)

Sadoulet and Carpenter (2001) argue that variables proxying for matching frictions include indicators of the degree of asymmetric information among different members of a group, proxies for the ability to monitor and screen the activities of the different members in a group, and variables on the available borrowing options. From our data set we select the following list of variables related to monitoring, screening, the available information about each other and the possibility to obtain credit.

1) *BORN*: a dummy variable with a one if the borrower is born in the village, zero otherwise
2) *KNOW*: a dummy variable with a one if the borrower knew the members well before meeting them in the group, zero otherwise
3) *INTEG*: a dummy variable with a one if the borrower knew about the behavioural integrity of all current group members before the formation of the group, zero otherwise
4) *ACTIV*: a dummy variable with a one if the borrower knows what the (daily) economic activities of the other group members are, zero otherwise
5) *PURP*: a dummy variable with a one if the borrower knows for what purpose the other group members acquired their last loans

6) *SEL*: a dummy variable with a one if the borrower approximately knows the weekly sales of the other group members, zero otherwise
7) *NUMBER*: the amount of members of the group
8) *LDIST*: the logarithm of the average distance of the business of the borrower from that of the other group members
9) *VISIT:* a dummy variable with a one if the members visit each other regularly, zero otherwise.
10) *PROBLEM:* a dummy with a one if the borrower has had problems in repaying debt before, zero otherwise.
11) *OTHER*: a dummy with a one if the borrower has other sources of credit, zero otherwise
12) *ACORD:* a dummy variable with a one if the group belongs to the *SZSCS (ACORD)* system, 0 otherwise
13) *CHANGE*: a dummy variable with a one if the borrower has participated before in another group, zero otherwise

From this list of variables, *BORN*, *KNOW,INTEG*, *ACTIV*, *PURP* and *SEL* primarily refer to social ties and the amount of information members have about each other. Some of these variables deal in particular with the available information before forming the group (especially *KNOW* and *INTEG*, and to some extent *BORN*), others refer to information after the group has been formed (*ACTIV*, *PURP* and *SEL*). An increase in value of one of these indicators implies more information about each other and probably stronger social ties. *NUMBER*, *LDIST* and *VISIT* have to do with the (possibility of) monitoring and screening each other's activities. More visits among members, and a lower distance between members probably increase screening possibilities. More group members tend to increase monitoring efforts, but there is also more scope for free riding. *PROBLEM* and *OTHER* refer to possibilities to obtain credit from other sources. *OTHER* directly measures whether a borrower has been able to raise funds from other sources than the microfinance institution. *PROBLEM* measures repayment problems in the past, and may give an indication of future possibilities to raise credit. *ACORD* and *CHANGE* are not directly related to the issues mentioned so far, but, as will become clear later, they have been included since they are highly correlated with one of the other indicators from this list.

First-best risk (X)

We assume that *first-best* risk can be picked up by variables that are directly related to the socio-economic situation of the borrower. We consider the following variables:

14) *LINC:* the logarithm of total monthly income
15) *AGE*: the age of a borrower
16) *GENDER:* a dummy with a one for a male, and a zero for a woman
17) *ILLIT:* a dummy with a one if the borrower is illiterate, zero otherwise
18) *PRIM*: a dummy with a one if the borrower has primary education, zero otherwise
19) *SEC*: a dummy with a one if the borrower has secondary education, zero otherwise
20) *LEADER*: a dummy with a one if the borrower is a group leader, zero otherwise
21) *MUSLIM*: a dummy with a one if the borrower is a Muslim, zero otherwise.

<Insert Table 2 about here>

Table 2 provides information on the zero/ one dummies. The table shows that about half of the borrowers still live in the village they were born. A substantial number of the borrowers knew each other before forming the group. Also, most borrowers have some knowledge about the activities of the other members of the group. Nevertheless, there is only a small fraction of the total group of borrowers that knows the approximately weekly sales of other borrowers. About 28 % of the borrowers admitted to have had repayment problems. Only 18 borrowers reported that they have other sources of credit, in addition to the micro credits. Moreover, almost nobody ever applied for a bank credit (only 14 borrowers did). For six of them, the bank refused a loan (the latter information is not given in the table). The total sample consists of 351 borrowers, of which 167 are borrowers from *SZSCS* and 184 from *SCP*. In Eritrea there are six zones. The data comes from four zones. In two zones

Eritrea only recently started to set up microfinance groups. The *SZSCS* only operates in the southern zone, the *SCP* all over the country.

The majority of the respondents are illiterate or with only reading and writing abilities. Out of the total 32 % admitted that they are illiterate and 36 % have only primary school education. Secondary graduates include only 5 % of the data. About 20% of the respondents are Muslim, the rest are Christian. There are 155 women and 196 men in the data set.

Table 3 provides data on the remaining independent variables.

<insert Table 3 about here>

The table shows that the average borrower is 46 years old, with an average monthly income (*INC*) of 1017 Nakfas. Trading is the main occupation of the majority of the borrowers (63%), followed by farming (17%). The remainder is distributed between services, daily labourers, and others. Often borrowers have different occupations at the same time, for instance, food vending and a traditional restaurant. The borrowers sell articles ranging from food items to clothing and provide services such as the provision of hot meals, pubs, local beverages and teashops (latter information is not in table). The number of members per group varies between 3 and 8, with an average of 4. In the median group, 60% is woman. The average distance between group members' business is about 500 meters.

Regrouping of the variables

The concepts matching frictions and first-best risk are latent variables, which are not directly observable. Above, we have selected a group of variables that is assumed to be related to matching frictions, and a group of variables that is assumed to be related to first-best risk. In order to better account for the high collinearity between some of the variables within the two groups, and in order to test whether we can reduce the number of independent variables by constructing a smaller amount of new composite variables, we performed a multiple factor analysis (*MFA*).

We started by applying a factor analysis on the indicators of the group of variables related to matching frictions. The analysis suggests that 11 indicators in this group can be decomposed into 3 underlying factors. The two remaining indicators (*PROBLEM* and *OTHER*) are left out of this analysis since they have very low factor loadings, even if more underlying factors are allowed for. The factor loadings of the analysis are given in Table 4.

<insert Table 4 about here>

The first factor mainly has to do with *KNOW* and *INTEG*, suggesting that the underlying factor in this case relates to information members have about each other before they formed a group. ACORD and NUMBER mainly determine the second factor. *NUMBER* has a negative factorloading, which suggests that, with respect to our sample, the average amount of members in credit groups from the *ACORD* (*SCSZS*) system is lower than that of the *SCP* microfinance system. A closer look at the data set confirms this: the average number of members in credit groups from the *SCP* is 5.2, whereas it equals 3.6 for the *ACORD* (*SCSZS*) system. The positive factor loading on *VISIT* suggests that members of credit groups from the *ACORD* system visit each other more regularly than those of the *SCP* system. The third factor mainly has to do with *PURP* and to a lower extent with *ACTIV*. This gives the impression that in this case the underlying factor relates to information members have about each other's business, after the group has been formed.

In the remainder of the analysis we will use the three factors, instead of the 11 original indicators. We interpret *FACTOR1* and *FACTOR3* as factors that primarily have to do with the asymmetry of information among group members. *FACTOR1* picks up information before forming the group, *FACTOR3* picks up information after the group has been formed. *FACTOR2* primarily relates to being a member of a credit group within the *ACORD* microfinance system. This factor might be important for risk taking since it strongly correlates with the number of members within a group. This gives information on a possible peer monitoring effort. Armendariz de Aghion (1999, proposition 3, p.95) states "A larger group size tends to increase peer monitoring effort, due to a joint-responsibility, a cost-sharing, and a commitment effect. However… a larger group size (also) increases the scope for free riding in debt-repayment decisions”.[5]

We also tried a factor analysis on the indicators for first-best risk. However, here the factor analysis showed that it is not possible to combine the indicators into a smaller group of underlying factors. The number of factors that has to be taken into account to accept the null hypothesis of enough factors is almost equal to the original amount of indicators. Therefore, we decided to proceed with the individual first-best indicators in the remainder of the analysis.

7. Estimating risk

The next step in the analysis is to examine the possible empirical relevance of our matching frictions and first-best risk variables for explaining risk of a borrower's liquidity strategy. In other words, the next step is the estimation of equation (4).

The dependent variable is the proxy for risk, *r,* which we have constructed. The independent variables are the 8 first-best risk indicators, the three factors related to matching frictions, and the remaining two variables (*PROBLEM* and *OTHER),* which are also related to matching frictions. To examine non-linear effects we also tried quadratic terms, but, except for the quadratic term of *LINC* (*LINC2),* none of them appeared to be significant, and hence were left out of the analysis.

The constructed dependent variable is censored between 0 and 1. Therefore, we estimate with the *TOBIT* estimation technique with left and right censoring (using *NORMAL* distribution of error terms). We also present ordinary least squares (*OLS*) estimates, to test for differences in outcome due to different estimation techniques. The estimation results are presented in Table 5

<insert Table 5 about here>

Equations 1A and 1B show that *LINC, LINC2, LEADER, SEC, PROBLEM* and *FACTOR2* significantly affect risk behaviour. Since *LINC* has a significantly negative coefficient and *LINC2* a significantly positive coefficient, there seems to be a non-linear relationship between the income of a borrower and his risk behaviour. For low income levels, an increase in income lowers risk, whereas it increases risk after a certain threshold level of income has been passed. Positive significant coefficients for *LEADER, SEC* and *PROBLEM* suggest that a group leader takes more risk than a normal group member, that members who are more educated take more risk, and that members who have had payment problems in the past also take more risk. The negative coefficient for *ACORD* implies that borrowers in a borrowing group belonging to the *ACORD* system take less risk. The underlying reason probably is that the number of members in credit groups belonging to the *ACORD* system is lower. Larger groups may lead to more risk taking of the individual members, possibly due to a better scope for free riding. These results hold for both the *OLS* and *TOBIT* estimates.

In equations 2A and 2B the regressions are repeated by ignoring the insignificant terms. These regressions confirm the results suggested by equations 1A and 1B. Finally, we re-estimate the equations by replacing *PROBLEM,* by *APROBCRED* (equations 3A and 3B). *APROBCRED* measures the amount of money that was involved when the borrower had problems repaying the debt, as a percentage of the size of the loan in the previous loan cycle. This indicator serves as an alternative indicator for *PROBLEM*. The results of these regressions again confirm the basic message of equations 1A and 1B.

Since *FACTOR2* mainly has to do with three indicators, *ACCORD, VISIT* and *NUMBER,* we also perform OLS and TOBIT regressions in which *FACTOR2* is replaced by one of these individual indicators. The regression results show that each of these individual terms, with the exception of the OLS estimate for *NUMBER*, are significant. Being a borrower from a credit group associated with the *ACORD* system has a negative effect on risk taking. The same holds for more visits among members of a credit group. An increase in the number of members of a credit group enhances risk taking of an individual borrower. The results are not presented for reasons of space, but can be obtained on request.

We are now able to come up with an estimate of $\overline{r_i^*} = X_i \overline{\alpha}$ and $\overline{\beta f_i} = f_i \beta$ (equations 5 and 6, above). For this we use the estimation results of equation 2B (the TOBIT estimates) presented in Table 5. As we have explained before, we argue that the variables that are related to the socio-economic situation (*i.e. LINC, LINC2, SEC* and *LEADER*) determine the risk choice in a frictionless world. The other variables (*PROBLEM* and *FACTOR2)* are primarily related to matching frictions. By using the estimated coefficient of equation 2B (Table 5) we can now come up with an estimate of $\overline{r}_i^*$, which we name *FIRSTBEST* and $\overline{\beta f_i}$, which we name *FRICTION*.[6]

8. Heterogeneity

The final step in the analysis is to estimate the heterogeneity equation (equation 7). For this we first need to develop a measure of risk heterogeneity.

The measure for risk heterogeneity:

In line with Carpenter and Sadoulet (2001) we measure risk heterogeneity (h_i) by:

$$h_i = \left[\sum_{r_j \in G_i} \frac{(r_i - r_j)^2}{(N_i - 1)} \right]^{0.5} sign(r_i - \overline{r_i})$$, where $\overline{r_i}$ is the mean risk in *i*'s group G_i.[7]

Table 6 gives descriptive statistics of *h*. Figure 2 graphs heterogeneity by means of kernel distributions.

<Insert Table 6 about here>

The graph clearly show that heterogeneity in almost all cases differs from zero. This seems to imply that we have to reject the hypothesis of homogeneous matching since with homogeneous matching the risk heterogeneity within groups should be equal to zero. However, it may be the case that this heterogeneity is caused by matching frictions, an issue we will examine by estimating equation 7.

Estimation results

The estimates of the heterogeneity equation are presented in Table 7. [8] Again we use the *OLS* as well as the *TOBIT* estimation technique. The dependent variable in the regressions is our proxy for heterogeneity (h). It appears that the coefficient for *FIRSTBEST* is significantly different from zero at the 99% level, strongly suggesting that homogeneous matching will not take place, even if the estimates are controlled for matching frictions.

<Insert Table 7 about here>

9. Conclusions

We conducted a survey in 2001 among members and group leaders of borrowers who accessed loans from two microcredit programs in Eritrea. Using the results from this survey, this paper aims to provide new insights on the empirical relevance of the homogeneous matching hypothesis for microcredit groups in Eritrea. A better insight about how groups are formed and whether these groups are homogeneous is extremely important for our understanding of the working of microcredit programmes. The result of our analysis can be used as input, or as intermediate result, for an analysis on repayment performance of joint liability schemes versus individual liability debt contracts.

An important part of the methodology to test for homogeneous matching consists of estimating risk behaviour. This analysis suggests that there is a non-linear relationship between the income of a borrower and risk taking. Below a certain threshold level of income, an increase in income will lead to less risk taking, whereas an increase in income will increase risk taking above a certain level of income. We also find that group leaders take more risk than normal group members, that better educated borrowers take more risk, and that borrowers that have had payment problems in the past will take more risk. Moreover, we find some evidence that borrowers in larger groups will take more risk than borrowers in smaller groups.

Concerning the homogeneous matching hypothesis, our results strongly indicate that groups are formed heterogeneously. Most importantly, we do not find support for the matching frictions hypothesis, in the sense that even if we control for matching frictions, credit groups in Eritrea do not seem to consist of borrowers of the similar risk type. The implication of this finding for repayment behavior is not clear at forehand. However, our result seems to be bad news for those who argue that group lending may reduce problems of adverse selection. In some theoretical papers it has been argued that incentive compatible separating equilibria will result if a lender offers different types of debt contracts, with varying components for joint liability. By choosing a particular debt contract, the borrower will signal its type and hence the asymetric information and consequently the adverse selection problem will be solved. However, this result is based on the homogeneous matching hypothesis.

Of course, some reservations with respect to our main conclusions can be made. For instance, the classification of variables in a group that primarily deals with matching frictions, and a group of variables dealing with first-best risk determinants may be criticised. In addition, our variables *FIRSTBEST* and *FRICTION* are constructed variables, and therefore are measured with error. This may biase the estimates of the coefficients. Moreover, the measure of risk we use may not be the most accurate measure for risk taking. There may exist other measures of risk that are better proxies. It may then be the case that using another measure for risk will lead to homogeneous matching, instead of the heterogeneous matching we found by using our measure for risk. More research on these issues is needed. Nevertheless, given the data we have, and taking into account all possible drawbacks of the methodology used, we think that our analysis, at the least, suggests that the commonly held assumption of homogeneous matching can not be confirmed for the case of Eritrea. If one accepts that groups are formed heterogeneously, an important issue is then to examine why this is so. A possible reason brought forward in some recent papers is the insurance that risky and safe borrowers may provide. The models behind the homogeneous matching hypothesis assume that borrowers are risk neutral and that project returns do not covary. This implies that in these models there is no possibility to gain from economies of risk pooling. However, if borrowers are risk averse and project returns are not independent, then a borrower may gain by grouping with another borrower if the project returns of the two borrowers are negatively correlated. This may then imply that heterogeneous matching is be the optimal outcome.

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Appendix: List of variables

ACTIV: a dummy variable with a one if the borrower knows what the (daily) economic activities of the other group members are, zero otherwise
ACORD: a dummy variable with a one if the group belongs to the *SZSCS (ACORD)* system, 0 otherwise
AGE: the age of a borrower
BORN: a dummy variable with a one if the borrower is born in the village, zero otherwise
CHANGE: a dummy variable with a one if the borrower has participated before in another group, zero otherwise
DIST: the average distance (in meters) of the business of the borrower from that of the other group members
h: the measure for risk heterogeneity. Measured as:

$$h_i = \left[\sum_{r_j \in G_i} \frac{(r_i - r_j)^2}{(N_i - 1)} \right]^{0.5} sign(r_i - \overline{r_i}) \, ,$$

GENDER: a dummy with a one for a male, and a zero for a woman
ILLIT: a dummy with a one if the borrower is illiterate, zero otherwise
INTEG: a dummy variable with a one if the borrower knew about the behavioural integrity of all current group members before the formation of the group, zero otherwise
LDIST: the logarithm of the average distance of the business of the borrower from that of the other group members
KNOW: a dummy variable with a one if the borrower knew the members well before meeting them in the group, zero otherwise
LEADER: a dummy with a one if the borrower is a group leader, zero otherwise
MUSLIM: a dummy with a one if the borrower is a Muslim, zero otherwise.
LINC: the logarithm of total monthly income
NUMBER: the amount of members of the group
OTHER: a dummy with a one if the borrower has other sources of credit, zero otherwise

P : loan payment due per month

PRIM: a dummy with a one if the borrower has primary education, zero otherwise

PROBLEM: a dummy with a one if the borrower has had problems in repaying debt before, zero otherwise.

PURP: a dummy variable with a one if the borrower knows for what purpose the other group members acquired their last loans

r : the risk measure, calculated as $r_i = \frac{P_i - S_i}{P_i}$, for $P_i \geq S_i$.

and $r_i = 0$ for $P_i < S$

S : the amount the borrower reported having saved one week before the due data

SEC: a dummy with a one if the borrower has secondary education, zero otherwise

SEL: a dummy variable with a one if the borrower approximately knows the weekly sales of the other group members, zero otherwise

VISIT: a dummy variable with a one if the members visit each other regularly, zero otherwise.

Source: Unless stated otherwise, all variables are obtained via a survey (personel interviews) in 2001 among members and groupleaders of credit groups in Eritrea. The survey is done in four of the six zones of Eritrea and contain credit the two microfinance institutions in Eritrea (the Saving and Credit Programme, *SCP*, and the Southern Zone Saving and Credit Scheme, *SZCS* .

Table 1: Information on Credit and Risk

	Credit Size	*P*	*S*	*r*
Mean	3961	422	356	0.17
Median	3500	380	300	0.09
Maximum	8500	2320	2080	1.00
Minimum	750	71.25	0.00	0.00
Std. Dev.	1802	315	272	0.213
Skewness	0.468	2.714	2.440	1.967
Kurtosis	2.406	13.008	12.257	7.761
Jarque-Bera	17.97	1895.87	1601.76	557.80
Observations	351	351	351	351

Note: for a list of variable see the Appendix. All values (except for *r*) are in Nakfas. The Jarque-Bera statistic is a test for normality. The statistic has a χ^2 distribution with 2 degrees of freedom under the null hypothesis of normally distributed errors.

Table 2: Variables explaining risk: Zero-One dummies

	No. of observations with 1 (% total)	No. of observations with 0	Total No. of observations
BORN	179 (51)	172	351
KNOW	287 (82)	64	351
INTEG	290 (83)	61	351
ACTIV	307 (87)	44	351
PURP	333 (95)	18	351
SEL	19 (5)	332	351
VISIT	265 (75)	86	351
PROBLEM	60 (17)	291	351
OTHER	18 (5)	333	351
ACORD	167 (48)	184	351
CHANGE	35 (10)	316	351
ILLIT	111 (32)	240	351
PRIM	128 (36)	223	351
SEC	19 (5)	332	351
LEADER	102 (29)	241	351
MUSLIM	70 (20)	281	351
GENDER	155 (44)	196	351

Note: See Table 1.

Table 3: Other variables explaining risk

	INC	*AGE*	*DIST*	*NUMBER*
Mean	1017	46	499	4
Median	1000	45	200	4
Maximum	13000	77	5000	8
Minimum	300	18	5	3
Std. Dev.	752	11.67	863	1.32
Skewness	11.661	0.002	3.52	0.66
Kurtosis	185.24	2.65	17.01	2.80
Jarque-Bera	493661	1.76	3595	23.87
Observations	351	351	351	325

Note: see Table 1

Table 4: Factorloadings for factor analysis on matching frictions variables

	FACTOR1	*FACTOR2*	*FACTOR3*
ACORD	-0.146	0.916	0.129
BORN	0.275	-0.227	-0.021
CHANGE	0.018	0.236	-0.019
KNOW	0.923	0.038	0.208
INTEG	0.935	0.050	0.202
LDIST	-0.176		-0.025
ACTIV	0.226	-0.093	0.376
PURP	0.058	0.120	0.733
SEL	0.102	0.185	0.048
VISIT	0.152	0.323	0.306
NUMBER	0.077	-0.632	0.019
Chi square Statistic: 24. 7; 25 Df; p-value: 0.479; CUMVAR=0.394			

Note: Factor loadings smaller than 0.01 are not reported. Df denotes the degrees of freedom. CUMVAR gives the cumulative variance explained by the factors taken into account. The factor analysis is done on 323 observations (the common sample of all indicators. Observations refer to groups of both microfinance institutions). The Chi square Statistic is a test of the hypothesis that 3 factors are sufficient versus the alternative that more are required. Df: degrees of freedom. P-value is the probability of being wrong when the null hypothesis is rejected (the plausibility of the null hypothesis. So, the smaller is the P-value, the less plausible is the null hypothesis). See the Appendix for a list of variables.

Table 5: Estimating risk

	1A	1B	2A	2B	3A	3B
Method	**OLS**	**TOBIT**	**OLS**	**TOBIT**	**OLS**	**TOBIT**
LINC	-0.866 (-2.93)	-1.224 (-3.48)	-0.880 (-3.05)	-1.260 (-3.63)	-0.487 (-2.19)	-0.790 (-2.77)
LINC2	0.055 (2.73)	0.078 (3.31)	0.056 (2.86)	0.080 (3.48)	0.029 (1.93)	0.048 (2.51_
AGE	0.0002 (0.22)	0.0003 (0.21)				
GENDER	-0.016 (-0.63)	-0.029 (-0.84)				
ILLIT	-0.029 (-0.96)	-0.037 (-0.91)				
PRIM	0.004 (0.16)	0.0020 (0.06)				
SEC	0.111 (2.40)	0.149 (2.39)	0.116 (2.78)	0.157 (2.72)	0.116 (2.85)	0.148 (2.59)
LEADER	0.0585 (2.70)	0.073 (2.46)	0.060 (3.00)	0.074 (2.62)	0.042 (2.25)	0.049 (1.91)
MOSLIM	0.012 (0.40)	0.019 (0.47)				
PROBLEM	0.320 (8.35)	0.386 (8.38)	0.321 (8.53)	0.386 (8.47)		
APROBCRED					0.399 (6.72)	0.540 (7.61)
OTHER	0.0028 (0.06)	-0.0049 (-0.08)				
FACTOR1	-0.00076 (-0.07)	0.0078 (0.50)				

FACTOR2	-0.022 (-2.07)	-0.049 (-3.16)	-0.022 (-2.13)	-0.050 (-3.25)	-0.016 (-1.73)	-0.037 (-2.74)
FACTOR3	-0.006 (-0.47)	-0.011 (-0.68)				
CONSTANT	3.443 (3.18)	4.734 (3.64)	3.480 (3.28)	4.846 (3.78)	2.092 (2.54)	3.188 (3.03)
adj. R^2	0.39	0.40	0.40	0.41	0.49	0.53

Note: the amount of observations is 323 for all regressions. t-values (z-values for Tobit) based on White Heteroskedasticity-Consistent Standard Errors (for the OLS regressions) and QML (Huber/ White) standard errors between parantheses. The Tobit estimates are done with left (0) and right (1) censoring; there are 94 left censured observations and 10 right censured observations. See the Appendix for a list of variables.

Table 6: Heteogeneity

	h
Mean	-0.005
Median	-2.78E-17
Maximum	1.00
Minimum	-1.00
Std. Dev.	0.265
Skewness	0.115
Kurtosis	5.227
Jarque-Bera	72.65

Note: see the Appendix for a list of variables

Table 7: Estimating heterogeneity

	1	2
METHOD	*TOBIT*	*OLS*
FIRSTBEST ($\bar{r}_i^*$)	0.663 (3.20)	0.660 (3.19)
FRICTION ($\overline{\beta f_i}$)	0.623 (5.54)	0.620 (5.52)
CONSTANT	3.129 (3.13)	3.115 (3.13)
adj R^2	0.15	0.16

Note: the amount of observations is 323 for all regressions. t-values (z-values) for *OLS (*for *TOBIT)* between paranthesis (based on White Heteroskedasticity-Consistent Standard Errors and Covariances and Huber/White robust standard errors&ccovariances, respectively). In equation 1 there is 1 right and 1 left censored observation. See the Appendix for a list of variables.

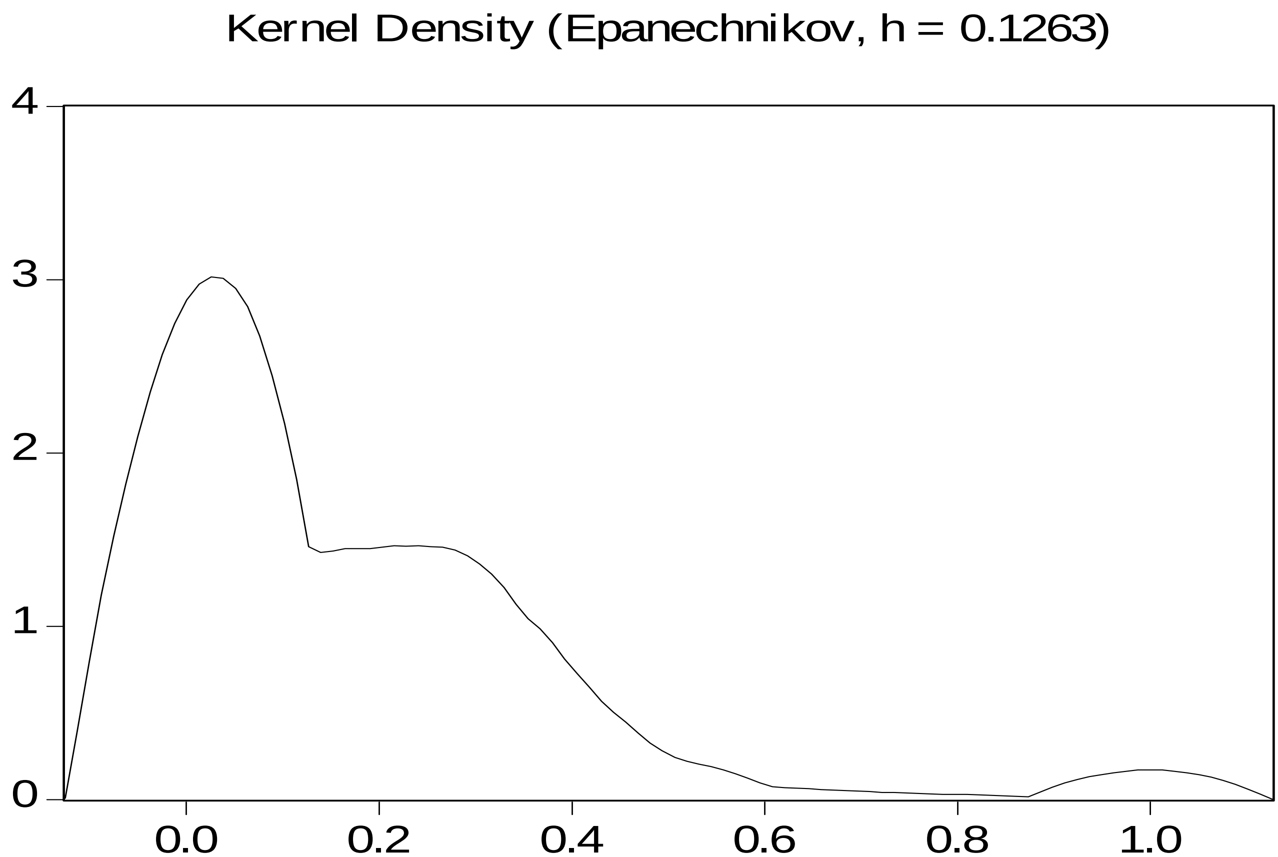

Figure 1: risk (r)

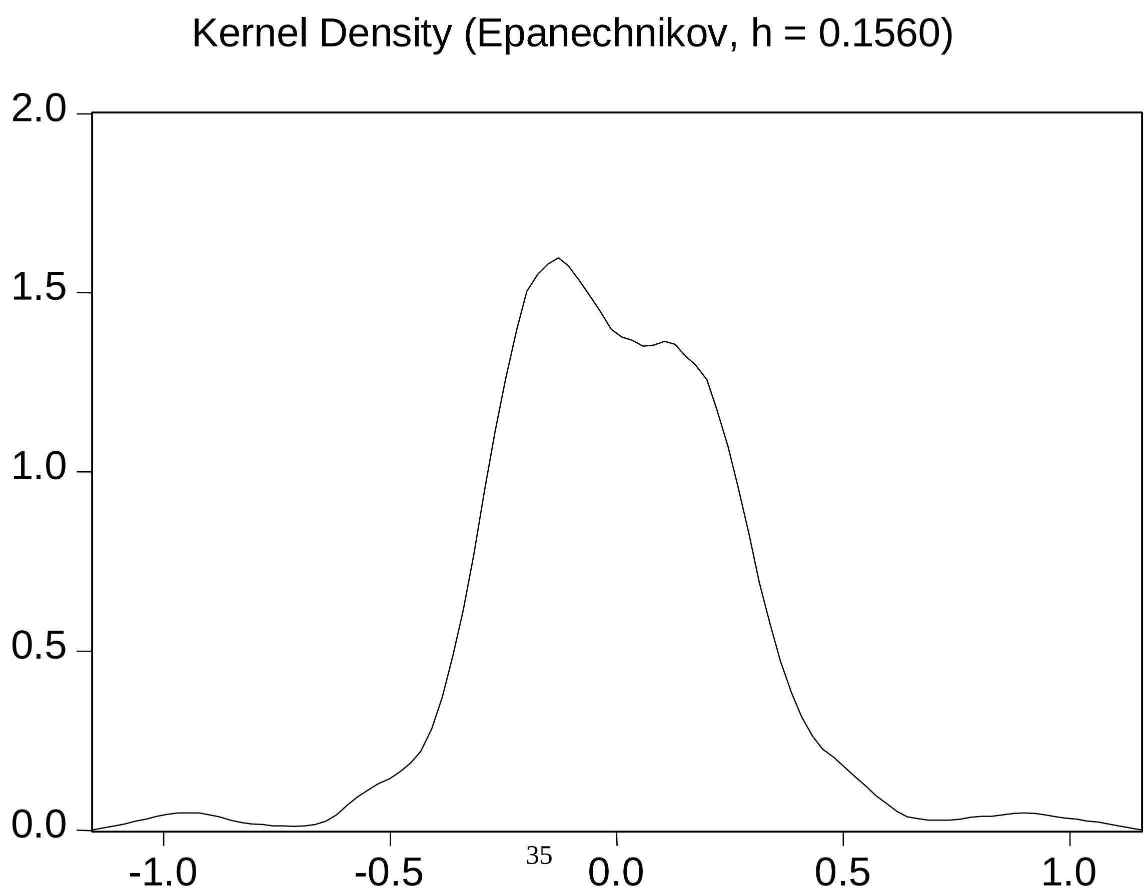

Figure 2: heterogeneity (h)

Endnotes

[1] See Armendariz de Aghion and Morduch (2000) for microfinance practices beyond group lending.
[2] Detailed information on the questionnaire can be obtained on request.
[3] Sadoulet and Carpenter (2001) consider the three last dates before the repayment date since repayments in their case take place once per week. In our case loan payments are once per month.
[4] Note that Sadoulet and Carpenter use the sum of expected sales in the last three days before the due date as the scaling factor, instead of P_i. Our questionnaire also contains a question on the expected sales in the last days (week in our case) before the due date. However, since the answers to this question were totally unreliable we decided to scale by P_i .
[5] Note that in Armendariz de Agion (1999) groups are exogenously given. In practice, there is a tradeoff between group size (monitoring effort) and benefits of size (diversifation, easier to cover one defaulting partner). Group size is thus endogenous. We ignore this problem in our analysis.
[6] We assume that the conditional mean ($E[y_i]$) of the TOBIT regression equation $y_i = \beta x_i + \varepsilon_i$. equals $K_i x_i$. If all independent variables are taken into account, this forecasts the so-called expected *latent variable.*
[7] We also used a measure for heterogeneity that is not adjusted for having a risk above or below the mean risk. This gave qualitatively the same results.
[8] It should be noted that the variables *FIRSTBEST* and *FRICTIONS* are measured with errors. OLS (and Tobit) estimates of the heterogeneity equation may therefore be biased. A possible solution, used by Sadoulet and Carpenter (2001) is to estimate the heterogeneity equation with instrumental variables. However, due to a lack of candidates for instruments in our sample, we decided to rely on the OLS estimates.