Repayment Performance in Group Lending: Evidence from Jordan

Moh’d Al-Azzam\textsuperscript{a}

Sudipta Sarangi\textsuperscript{b}

Abstract: Group lending has been proposed as a tool for alleviating poverty in developing countries. The success of group lending has been attributed to its ability to mitigate asymmetric information and enforcement problems in the credit market. We use data from a survey of 160 borrowing groups of the Microfund for Women in Jordan to test the effect of screening, peer monitoring, group pressure, and social ties on borrowing groups’ repayment behavior. The data suggest that delinquency is reduced by screening, peer monitoring, group pressure, and social ties.

Keywords: Group Lending, Adverse Selection, Moral Hazard, Enforcement.

JEL Classification: D82, G29, O12

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\textsuperscript{b} Department of Economics, Louisiana State University, Baton Rouge LA, 70803
Phone: (225) 578-3805, Fax: (225) 578-3807
Email: malazz1@lsu.edu

\textsuperscript{b} Department of Economics, Louisiana State University, Baton Rouge, LA 70803
Phone: (225) 578-7193, Fax: (225) 578-3807
Email: sarangi@lsu.edu
1. Introduction

Finding the answer to world poverty probably features as top priority for humanity. According to World Bank estimates in 1999 about 1.2 billion people world-wide had consumption levels below $1 a day, and 2.8 billion lived on less than $2 a day. A key constraint that is believed to keep the poor in their state is the fact that they lack credit. Hence a major thrust of anti-poverty programs initially was to provide subsidized productive credit to the weaker sections of society. Yet, such poverty alleviation schemes adopted from the early 1950s through 1980s were largely unsuccessful. Loan repayments rates often were well below 50 percent, costs of subsidies for financing these programs were prohibitively high and much of the credit was diverted to the politically powerful, away from the intended recipients (Adams, Graham, von Pischke 1984). Consequently, their impact on poverty was virtually negligible.

In the last couple of decades however, a growing range of financial institutions that developed an alternative lending mechanism have turned around the received wisdom that lending to poor households is doomed to failure.¹ Microfinance institutions (MFIs) as these are called share a commitment to providing poor households with very small loans to assist them start productive activities or grow their current small businesses. MFIs extend credit to poor household through innovative use of information that potential borrowers may have about each other while maintaining high repayment rates and financial sustainability.² The hope is that much poverty can be mitigated by extending credit and financial services to poor households.

¹ Among these pioneer financial institutions are the Bangladesh’s Grameen Bank, BancoSol of Bolivia, and the Bank of Rakyat Indonesia where the repayment rates in these institutions are above 95%. See Morduch (1999) for a review of these microfinance institutions.
² In this literature financial sustainability refers to the ability of an MFI to cover all of its costs through interest paid by its clients, i.e., not having to resort to donors for funds.
In most developing countries poor households usually have no access to the formal banking system. The formal banking system has three major problems in extending credit to such borrowers: inability to assess the risk type of potential borrowers (screening), to ensure that the loan, once made, is utilized productively (monitoring) and to ensure the repayment of loans if borrowers are reluctant to do so (enforcement). Note first that the poor in general cannot meet the collateral requirements stipulated by the banks. Second, the inherently high cost to banks of screening and monitoring the actions of the poor and to enforce contracts may all contribute to the exclusion of the poor from the credit market.

One innovation for extending credit to the poor lies in group lending – lending to a self-selected group of entrepreneurs who are jointly liable for a loan. Since group members are jointly liable for a loan, group lending creates incentives for individual group members to screen out risky borrowers, monitor each others’ actions and enforce repayment. Essentially, by replacing physical collateral with a form of social collateral, it considerably lowers the cost of the loan for the lender. The borrowers have more information about each other and hence can successfully solve the asymmetric information problem that plagues the lenders.

While a host of theoretical explanations exist to account for the success of group lending programs, empirical research has lagged behind. In an attempt to fill the gap between the theoretical and empirical research, this paper examines the significance of screening, monitoring, group pressure, and social ties on borrower group performance. The data was obtained by the researcher himself through a survey of 160 groups carried out in cooperation with the Microfund for Women (MFW), a group lending institution, in Jordan.

The rest of the paper is organized as follows. Section 2 reviews the relevant literature in group lending, while section 3 provides an overview of microfinance in Jordan as well as a description of the group lending methodology of the MFW. Section 4 describes the data
collection process and the variable construction. In section 5 empirical results are presented with section 6 containing some concluding remarks.

2. Review of the Related Literature

The literature on group lending is quite substantial. Here I provide a brief overview of some of the theoretical papers. The last part of this review examines the small but growing number of empirical papers on this topic.

Credit rationing and collateral requirements are primarily responsible for the exclusion of poor borrowers from the credit market. As shown in the seminal paper by Stiglitz and Weiss (1981), liberalizing interest rates, or using collateral requirements to loosen credit rationing results in adverse selection and moral hazard problems. By definition the poor have limited supplies of tangible assets. Their likely failure to meet collateral requirements makes the lenders’ job of screening the poor borrowers a difficult mission. One innovation to extend credit to the poor that simultaneously addresses the asymmetric information problem and enforcement concerns lies in group lending; lending to self-selected groups of entrepreneurs who are jointly liable for a loan. Groups form voluntarily, and, while loans are made to individual in the group, all members of the group are held responsible for loan repayment by the entire group. Many theoretical papers have stressed group lending’s informational and enforcement advantages over individual lending. Since group members are jointly liable for loan repayment, group lending can achieve better screening to dilute adverse selection, induces peer monitoring to contend moral hazard and provides group members with incentives to enforce loan repayments (Ghatak and Guinnane 1999).³

Ghatak (1999) and Van Tassel (1999) are representatives of models that explore the adverse selection problem. They show how group lending can take advantage of the “inside”

³ This exhaustive survey also provides an excellent introduction to the theory and practice of group lending.
information that only borrowers have about each other, to draw in relatively safer borrowers. Note that these safe borrowers would otherwise have been excluded from the credit market under individual lending contracts because of the high interest rates necessary to cover risks. Thus, under asymmetric information lenders can use group lending methodology for screening borrowers, as safe borrowers group together and select group loans at low interest rates and risky borrowers group together and select group loans at high interest rates. As a result repayment rates and efficiency are higher under group lending than individual lending (Ghatak 1999).

Another strand of papers focuses on monitoring and moral hazard issues under group lending. Varian (1990) analyzed how borrowers mutually monitor each others’ projects to ensure the success of financed projects and how monitoring reduces some of the barriers and information asymmetry between the lender and the borrower. Stiglitz (1990) shows that group lending, via monitoring, alleviates the moral hazard issues involved in lending to those with no collateral. Stiglitz’s model shows how group lending can increase the choice of safer projects by inducing a borrower to encourage a partner to choose a safer project. Banerjee, Besely, and Guinnane (1994) show that the burden of moral hazard problem between a borrowing member and the lender falls on the monitoring members who are responsible for repaying the loan of the defaulting member. They show that with an increasing cost of monitoring, a monitor can impose higher penalties on the borrowing member in the case of default, giving the borrowing member an incentive to choose a safer project.

Another set of theoretical papers focus on the strategic default strategies of group members. In the Besely and Coate (1995) model borrowers choose whether to repay or not after realizing projects returns by comparing the repayment amount with the severity of the

If group members do not have complete information about each other, then group lending may not lead to any improvements in loan repayment rates. This has also been shown in Laffont and N’Guessan (2000).
official penalties imposed by the lender, and the unofficial penalties imposed by the other
group members and the community. They show that group lending can improve repayment
rates relative to individual lending given that social penalties are strong enough. Aghion
(1999) argues that monitoring and the threat of social sanctions can prevent strategic default
in group lending. In this model, a borrower can verify her partner’s true project returns at
some cost and inflict sanction upon default. I now move on to the empirical part of this
research.

One of the earliest empirical papers by Wenner (1995) used data from 25 Foundation for
International Community Assistance (FINCA) credit groups in Costa Rica to study group
lending as a means of transmitting information on borrower creditworthiness. The
relationship between repayment rates and explanatory variables was examined internally, that
is between members and the credit group and then externally, between the group as a whole
and FINCA, the credit institution. Wenner found that groups that screened on the basis of
an internal written code of regulations had better internal as well as external repayment rates
than those that did not. Also, groups that lived in better off towns in terms of infrastructure
had worse repayment performance indicating that those groups may have alternative credit
sources and value the FINCA services less.

Around the same time in another paper Sharma and Zeller (1996) investigated the
determinants of repayment performance of 128 credit groups belonging to three group-
based credit programs in Bangladesh. Their main findings include the significance of the
effect of risk diversification, credit rationing, screening, and social ties on repayment
performance. They found that high degree of credit rationing and unfulfilled credit demand,
improves repayment performance since it generates incentives for protecting higher
expected credit in the future. However, higher degree of credit rationing which renders the
loan size trivial worsens repayment. Not surprisingly, groups formed endogenously, where
screening is assumed to be more effective, were found to have better repayment rates
relative to groups formed by credit institutions. Social ties, measured as the proportion of
relative members in the group, has a negative impact on repayment supporting the
hypothesis that it might be difficult to impose sanctions on relatives, which dilutes the
enforcement process. Among other results, Sharma and Zeller also found that repayment
rates are negatively associated with larger loan sizes.

investigated the effect of intragroup risk pooling and social cohesion on the repayment rate.
The data used by Zeller was obtained from a random sample of 146 groups from six
different group lending programs in Madagascar. While most Malagasy households grow rice
in irrigated lowlands, rainfed uplands constitute more than half of the total landholdings in
the sample household. Returns from uplands are highly variable while returns from irrigated
lowlands are stable making uplands a risky asset while irrigated lowland a safe one.
Intragroup risk pooling, the degree by which group members diversify the group’s joint
portfolio of assets, is measured by the coefficient of variation of upland possessed by
members of the same group. Zeller’s results showed that repayment rate increases with more
diversification of the group’s joint asset portfolio. However, there is an optimal point of risk
pooling after which increased diversification leads to lower repayment rate because of higher
cost of monitoring. Therefore, the hypothesis that groups consisting of members with
homogeneous risk exposure have higher repayment rates was rejected. Social cohesion,
measured by counting the number of common characteristics among group members like
social class, ethnicity, neighborhood, friendship and kinship, is found to improve the
repayment rate.
Wydick (1999) analyzed the effect of peer monitoring, social ties, and group pressure on the provision of intra-group insurance, the mitigation of moral hazard within borrowing groups, and the group repayment performance. Using a sample of 137 borrowing groups of the Fundo Para o Desenvolvimento de Atividades Portuárias (FUNDAP) from in and around the rural towns of Quetzaltenango and Totonicapan in Guatemala, Wydick’s empirical results show that social ties have no effect in mitigating moral hazard within a borrowing group. They have a small effect on providing intra group insurance, and have no effect in improving repayment rates. Group pressure within groups exerts a significant effect in mitigating moral hazard, has a modest effect on the provision of intra group insurance, and has no effect on repayment rate. The empirical results show that peer monitoring is a primary factor in affecting group performance in terms of providing intra group insurance, mitigating moral hazard, and improving repayment rates. It is only peer monitoring that has a direct effect on repayment rates. Repayment rates are improved through different channels in urban versus rural areas. In urban areas, repayments rates are improved through the stimulation of intra group insurance via more intensive peer monitoring. In rural areas, groups enforce repayment by deterring moral hazard through willingness to apply social pressure.

More recently, Godquin (2002) tested the explanatory power of social ties, group homogeneity, social intermediation, dynamic incentives and loan characteristics (loan size and loan duration) on group’s repayment performance. Godquin used 1629 loan observations of borrowers from the Grameen Bank, Bangladesh Rural Advancement Committee (BRAC), and Bangladesh Rural Development Board (BRDB) from Bangladesh. Two repayment measures were used: repayment on time with a grace period of three months was used in the whole sample and repayment on time was used in the split sample (one regression by MFI). In this paper, Godquin tested and corrected for endogeneity of the
size and duration of the loan in the determination of repayment.\footnote{Godquin used private access to electricity and the number of weeks the borrower had to wait before receiving his loan as instrumental variables for loan size. For the duration of the loan, he used signature or personal guaranty required as primary collateral and the number of weeks the borrower had to wait before receiving his loan as instrumental variables.} Godquin found that the effect of social ties within group members on repayment is negative while the effect of social ties of group members out of the group is positive. Social intermediation and group homogeneity in terms of sex, education and age have no significant impact on repayment in the whole sample. In the split sample, social intermediation and group homogeneity showed mixed effects on repayment. Credit rationing, a measure of dynamic incentive, showed a positive effect on repayment in the split sample. Group size had a positive impact on repayment on time. While the loan size showed a negative impact on repayment before instrumentation, the instrumented size of the loan presented a positive impact.

In a comprehensive paper Ahlin and Townsend (2005; henceforth AT) develop and test the implications of four representative models of joint liability lending. Two of these models: Stiglitz (1990) and Banerjee, Besley, and Guinnane (1994; henceforth BBG) highlight moral hazard problems that can be mitigated through joint liability lending and monitoring. The third one, Besely and Coate (1995; henceforth BC) relates strategic default or limited enforcement model. The lender cannot fully enforce repayment and borrowers decide whether or not to repay by comparing the repayment amount with the severity of penalties imposed by the lender and the community. The fourth model to be tested is Ghatak (1999) which describes how the joint liability contracts can partially overcome the adverse selection problem. AT examined both the predictions of variables already included in these models, and predictions of additional variables they introduced in a general way. AT introduced the loan size in the BBG’s model, productivity in all four models, correlation of borrower output in Stiglitz, BC and Ghatak models, the degree of cooperation in the Stiglitz, BBG, and BC
models, the availability of outside credit in both the Stiglitz and BBG models. Variables considered in some or all models or introduced by AT include interest rate, loan size, liability payment, borrower productivity, screening ability, the ease of monitoring, the degree of cooperation, the availability of outside credit, and penalties for default.

The data used to test predictions regarding the determinants of the group repayment rate are from large cross section survey of 192 villages in Thailand conducted in 1997. The survey covers two contrasting regions; one enjoys a degree of industrialization and fertile land for farming; and the other is poorer and semi-arid. The survey data is from 262 joint liability groups of the Bank for Agriculture and Agricultural Cooperative (BAAC) and from 2880 households of the same villages. Nonparametric, univariate tests and multivariate logits methods were used to study the predictions of the models for repayment.

AT found that the joint liability payment amount has a negative effect on repayment rate which favors the Stiglitz and Ghatak models over BBG’s. This finding supports the fact that higher joint liability amount under ceteris paribus conditions acts as an additional tax on success, since only the successful borrowers pay it. Due to insufficient variation and potential endogeneity problems, no attempt was made to establish a relationship between interest rate and repayment rate and loan size and repayment rate. However, they find evidence that is in line with Ghatak’s inverted-U shape relationship between repayment rate and loan size. Education, a measure of productivity, improves repayment performance. This favors all four models. Their data does not reveal screening as a significant determinant of good repayment as predicted by Ghatak. Favoring the Stiglitz and Ghatak models, the covariance of output has a positive effect on repayment. The cost of monitoring variables show mixed results.
In the nonparametric comparisons and the fixed effects logit, the higher the percentage of group members living in the same village, the better was their repayment performance. On the other hand, the results show that the higher the percentage of relatives in the group, the lower the repayment. The first result favors BBG’s model while the second contradicts it. Default penalties show positive and significant effect on repayment which are in line with the BC model’s predictions. Outside credit options, the availability of village-run savings and loan institutions, are negatively and significantly associated with repayment performance. This finding is in line with the Stiglitz and BBG models. Finally, AT found that cooperation tends to worsen repayment rates favoring the BBG and BC models over the Stiglitz’s story. AT conclude that social structures that disable penalties can be harmful for repayment.

3. Microfinance in Jordan

3.1. Overview

The history of microfinance in Jordan started with the public sector provision of subsidized credit in 1959 by launching the Agricultural Credit Corporation (ACC). The ACC was founded for the purpose of providing loans, including micro loans, for the development of the agricultural sector. The first manifest microlending program was founded in 1965 by the Industrial Development Bank. Numerous microenterprise foundations were subsequently established: the General Union of Voluntary Societies in 1986, the Development and Employment Fund in 1992, the Orphan’s Fund in 1972, the UNRWA Microenterprise Credit Programme in 2002, the Noor Al-Husain Foundation (NHF) in 1985, the Near East Foundation, and the Jordanian Hashemite Fund for Human Development (Enterprise Development) in 1990. A new government sponsored bank – the National Bank for Financing Small Projects, known as the “Bank of the Poor”, is currently underway with expected subsidized credit provision. However, the client base, the market influence, and the
subsidized credit available to the public sector microcredit programs have been declining over the last several years. Instead a number of privately owned MFIs that engage in sustainable financing have stepped in to fill this gap.

The concept of sustainable microfinance was introduced in Jordan by the Save the Children (SC) in 1994, when they launched the Group Guaranteed Lending and Savings Programs (GGL). Encouraged by this success, a separate legal entity (the Jordanian Women’s Development Society) was established in 1996, which commenced operations and became the Microfund for Women (MFW) in 1999. Subsequently, three other microfinance institutions (MFIs) were also established: Jordan Micro Credit Company (JMCC) in 1999, Ahli Microfinancing Company (AMC) in 1999, and the Middle East Micro Credit Company (MEMCC) via Cooperative Housing Foundation in 1998. Support for the sustainable microfinance industry in Jordan is primarily achieved through the Access to Microfinance and Improved Implementation of Policy Reform (AMIR). The AMIR program is an innovative economic opportunity project funded by USAID and implemented in partnership with the Jordanian private sector and government. With technical assistance from AMIR, these four MFIs achieved operational and financial self-sufficiency by charging an interest rate that recover all costs on their demand driven products. 6

While the subsidized microcredit providers have a significantly higher share of the total amount of credit disbursed to microentrepreneurs, the newly established MFIs have a higher share of the total number of borrowers, close to 80%. A credit demand study in 2002 estimated the potential demand for microcredit at JD 220 million (JD 1 = $ 1.4). Based on effective demand, or ability to pay, the demand for microcredit was estimated at JD 86

6 Operational self-sufficiency is achieved by covering all administrative costs and loan losses from operating income and financial self-sufficiency is achieved by covering all administrative costs, loan losses, and financing costs from operating income after adjusting for inflation and treating all funding as if it had a commercial cost (Charitonenko and Kristalsky, 2004).
million concentrated in urban areas and registered businesses. According to that study, the
MFIs can potentially capture 90% of the market (AMIR Report, 2002). As of March 2004,
the four MFIs together were serving almost 17,000 clients for an outstanding portfolio of
almost JD 9.7 million. I now proceed to discuss the largest of these MFIs which is also the
data source for this study.

3.2. Microfund for Women

The Microfund for Women (MFW) started operations in 1996 under the name Jordanian
Women’s Development Society. MFW is registered as a non-profit limited liability company
with the Ministry of Industry and Trade since October 1999 and has a headquarter office
and 9 branch offices serving major cities in Northern and Central Jordan. Initially, MFW
exclusively targeted low-income female clients. Over the past three years, however, it has
been expanding to include more registered businesses and even men, with the limitation that
male borrowers cannot exceed 20% of the total client base. The vast majority of clients live
in highly urban areas and are easily accessible to MFW staff at low cost. MFW offers three
types of loans; group loans, individual loans and seasonal loans. Individual and seasonal
loans are approved and supervised by the headquarters while group loans are approved and
supervised in branch offices. Since our focus is on group loans, a description of their group
loan program is provided in Table 1.7

The Group Guaranteed Lending Product (GGL) offered by MFW utilizes the group lending
methodology, where individual borrowers themselves form a group that jointly guarantees
the loan to the group. The group members must know each other and respect the loan size
caps by cycle. There are also restrictions on who can form groups with whom. Within
groups, members may not be business partners or from the same family. The required group

7 All tables are at the end of the paper.
size is between 4-6 members, and the group loans on average, range between JD200 and JD500 per borrower. The initial loan size for all new members is on average JD200. The groups have the choice to make their repayments either in bi-weekly or monthly installments.

The MFW hold two basic meetings with the borrowing groups, one to fill initial forms and discuss policies and the second to define group members’ roles (leader and treasurer) and to review the loan contract orally. In the disbursement meeting at the MFW branch, clients are reminded of the contract policies. The group leader is appointed by the MFW and functions as an intermediary between the group members and the loan officers. The group leader and the treasurer keep the accounts of the group, collect the installment payments from the group members and transfer these installments to the MFW designated partner bank. Being a group leader or treasurer is a voluntary activity and does not generate any financial privileges.

To discourage delinquency, a late penalty of 3 JD per day, payable on the next payment date or at the end of the loan term are imposed. Delinquent cases are referred to court after 21 days. As of March 2004, MFW was serving 10,720 clients for an outstanding portfolio of JD 2.5 million. Since its inception, the MFW has been quite a success maintaining repayment rates above 98% in its group loans.

4. The Data Collection Process and Variable Description

4. 1. The Data

During the months of February through May of 2005 I carried out a survey of 160 randomly selected borrowing groups of the MFW in Jordan. Two of the MFIs in Jordan provide group loans, the MFW and the Jordanian Micro Credit Company (JMCC). The MFW started its

8 There were approximately 23 delinquent cases in court proceedings for the periods 2003 and 2004.
group lending program in 1996 while the JMCC started in 2004. The sample focuses only on the MFW group borrowers because the JMCC group lending program was newly introduced with the vast majority of the group borrowers having short history of repayment. The survey covered two provinces, Irbid (north) and Al-Rusaifa (mid-north). The reasons for choosing these two provinces are due to their geographical proximity to my place of residence and to the fixed budget and time I had. In Irbid, 84 groups were surveyed while in Al-Rusaifa the survey covered 76 groups. The survey took place at the MFW branch offices of Irbid and Al-Rusaifa. The MFW appoints a leader for each group who functions as an intermediary between the group members and the MFW loan officers. The official leaders of the groups were interviewed as they walked in into these branches for loan transaction related matters. Sitting at the MFW branch office and waiting for any group leader to show up guarantees that each possible group leader has the same probability of being selected in the sample. Three group leaders out of 163 refused to provide answers to the questionnaire. Data on the loan size, the number of continuing, old, and new members of each group, and the loan application dates were obtained from the MFW’s data base. Also obtained from the MFW’s data base are the number of installments, the due amount of installments, the due dates of repayment, the actual repayment amounts, and the repayment dates for each group.

4.2. Variable Description

4.2.1. Dependents Variables

We use two measures of repayment. Data on repayment were obtained from the MFW data base. Our first measure of repayment, Delinquency, is a binary dummy which is equal one if a group had at least one late repayment and zero if a group paid all installments on time up until the survey interview took place. The second measure of repayment is the sum of late
days of repayment for each group up until the survey interview took place. We call this measure *Delinquency Intensity*. The second measure gives a better idea of the overall repayment performance of the borrowing groups.

### 4.2.2 Independent Variables

In this section we divide the independent variables into five groups; control variables, screening variables, monitoring variables, social ties variables, and group pressure variables. The descriptive statistics of the dependent and the independent variables are summarized in Table 2.

**Control Variables**

When the survey took place, groups had different starting dates of receiving loans and therefore were at different stages of repayment. Time span of repayment performance is therefore not symmetric with some groups having only one month of repayment history to groups having eight months. Up until the interviews took place, forty eight percent of the groups had repaid the due installments on time (mean and median of repayment history during the current cycle are 5.96 and 8 respectively).\(^9\) The fact that only 48 percent of groups had repaid the due installment on time should not be viewed as a drawback against the MFW group lending program. Actual repayment rate at the end of the cycle is much higher. That is, while late repayment is common, default is not. On average, each group has 3 days of late repayment. The MFW charges a fixed amount of 3 JD per late day which is the first remedial action taken against the fail-to-pay-on-time groups.

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\(^9\) A loan cycle is the period between issuing the loan and the final installment repayment, ranges between eight to ten months.
The explanatory variables used are summarized in Table 2. \textit{Rephist} is the number of installments made or supposed to be made since the loan was issued. It reflects the repayment history for each group in the current loan cycle. If repayment occurs with some probability $p$ each month, then groups with a longer history are more likely to have late repayment. Toward the end of the cycle, however, groups are expected to improve their repayment performance to be eligible for another loan cycle. Therefore, the effect of repayment history is a non-linear. The log of repayment history ($\ln\text{Rephist}$) will be considered in the empirical analysis.

Stiglitz (1990) assumed that the expected utility of a risky project increases faster in loan size than that of a safe project. This assumption guarantees that risky projects become relatively more attractive as loan size increases. In Ahlin and Townsend (2005), when they introduced the loan size in BBG (1994) model, they conclude that higher loan has two opposite effects. Higher loan size increases the monitor’s liability and thus his incentive to monitoring. It also increases the expected interest cost to the borrower more than his expected output inducing him to choose riskier projects. The second effect dominates and probability of success declines. Ahlin and Townsend also introduced the loan size in Ghatak (1999) model. If groups are credit constrained, and as loan size increases, higher loan size means higher payoffs and borrowers are drawn from larger and safer pool. Further higher loan size indicates a lower cost of funds, which means borrowers are drawn from a more risky pool. Therefore, an inverted U shaped relationship characterizes the effect of loan size on repayment. In our study, \textit{Loansize} measures the group loan size in hundreds of JD. Following Ahlin and Townsend (2005), we consider the \textit{Loansize} and it is square \textit{Loansizesq}.

models predict that higher borrower productivity increases repayment rate. Group leaders were asked to classify each group member into one of 6 categories, whether the member can read, have elementary schooling, preliminary schooling, high schooling, two year college, or four year college. Values of 1 to 6 were assigned to these levels of education respectively. The average educational attainment is close to 3 which correspond to 9 years of actual schooling. Our measure of Productivity, $\text{Education}$, is a dummy variable that is equal to 1 if a group has an average educational attainment of 4 or above. This measure allows us to directly compare the repayment performance of groups with higher education to groups with lower education.

Both Stiglitz (1991) and BBG (1994) have predictions on the effect of outside borrowing options on repayment rates. Groups with more outside borrowing options will experience higher loan size (from the primary lender and from other outside options) giving group members greater incentive for risky projects. Our measure of outside borrowing options, $\text{Cropption}$, is the percentage of group members who have access to credit from individuals outside the group.\(^{10}\)

Repayment behavior may vary across the MFW’s branches. To capture any difference in repayment behavior of the borrowing groups across the two branches surveyed, we include a dummy variable equals to one if the group belongs to Al-Rusaifa’s Branch. We call this variable $\text{Branch}$.

While the MFW does not require assets ownership by the borrowing groups, such wealth indicators may improve the capacity of the groups to meet repayment requirements on time.

\(^{10}\) We prefer to use outside credit options from individuals outside the group rather than from commercial banks. Most group leaders were asked to answer a yes/no question of whether a particular group member has access to credit from commercial banks. Many leaders stated that they were providing answers to this question with high degree of uncertainty, guessing. The responses on whether a particular group member has access to credit from friends, relatives, etc. have been received and answered with much more comfort and confidence.
We use land ownership to capture the wealth effect on repayment behavior. *Land*, measured in hundreds of square meters, is the mean size of land owned by the group.

Cultural factors, like religion, may affect the repayment performance of groups. All group members interviewed in the sample were Muslims. We attempt to measure religion intensity across groups by considering the percentage of group members who pray five times a day. We call this variable *Religion*.

Group age, called *Groupage*, is the number of years since the groups took their first group loan. If each loan cycle reinforces the credit value to the borrowing groups, then one would expect the repayment performance to improve at each successive loan cycle. But if groups envision their relationship with the lending program as transitory, then one would expect the repayment performance to worsen on later loan cycles. Group age also can be a proxy for experience. Groups with longer history of borrowing are expected to have better handling and management of loans and repayment. The expected sign on *Groupage* is therefore ambiguous.

**Screening Variables**

Ghatak (1999), Van Tassel (1999) and Ghatak and Guinnane (1999) presented models where group lending, via screening, can mitigate problems created by adverse selection. The key is that group formation displays positive assortative matching under group lending schemes. A successful safe borrower is more likely to pay the joint liability payment if he teams with a risky borrower but less likely to pay the joint liability payment if he teams with a safe borrower. Therefore, any safe borrower prefers to team with another safe borrower to form a group. Our measure for screening, *Screen*, is a dummy that is equal one if the group has ever rejected a borrower who would like to join the group. In adverse selection models, and as necessary prerequisite for screening to function, borrowers are assumed to know each
other’s type in terms of risk. To measure this we use a dummy variable, $knowtype$, that takes a value of one if members know the quality and sales of each other’s occupation.

**Monitoring Variables**

Armendariz and Beatriz (1999), Ghatak and Guinnane (1999) and Banerjee, Besley, and Guinnane (1994) presented models in which peer monitoring mitigates moral hazard behavior of individual group members. Stiglitz (1990), in another peer monitoring model, deduce that the repayment performance in group lending programs is positively related to the members’ homogeneity with respect to their projects’ riskiness. Cost of monitoring is measured using different proxies. $samebus$ is the group occupational homogeneity. It is the probability that two chosen group members have the same occupation. The more homogeneous the group is, the easier to monitor. Based on the MFW 2003 annual report, the sector distribution of the MFW clients’ enterprises during 2003 is as the following: 67% trade, 19% handicrafts, 7% production and manufacturing, 5% services, and 2% agriculture and live stock. Similar distribution was obtained from the survey data. Namely, 65.9% of the group members are involved in trade, 21.7% in handicraft, 5.8% in production and manufacturing, 4% in services, and 2.6% in agriculture and live stock. The majority of the empirical literature focuses on areas where the agricultural sector is the dominant, (Ahlin and Townsend (2005), Sharma and Zeller (1996), and Zeller (1998)). These studies focus on the risk pooling characteristic of occupational homogeneity while we focus on the cost of monitoring one. While it is easy to justify the correlation in output in the agricultural sector, it is more challenging to justify it in other sectors like trade. Group members with the same line of trade business (clothes trade, for example) may yet have different returns.

The second measure of cost of monitoring, $related$, is the percentage of members in the groups that are related to each other. Due to higher flow of information among relatives, the
higher the percentage of relatives is, the easier to monitor and therefore the less moral hazard. Models like BBG (1994) relate monitoring to imposing penalties. Therefore, while it might be easier for a group member to monitor her relative partner in the group, it might be difficult to impose penalties on her as well.

We also attempt to measure the cost of monitoring by looking at the percentage of group members who have phone services. The hypothesis here is that the higher the percentage of members with phone services, the easier the flow of information and therefore monitoring. *Phone* measures the percentage of members in a group that have access to either land or cell phone services.

**Group Pressure Variables**

Besely and Coate (1995) stressed the importance of group pressure against defaulting members to reduce moral hazard in a borrowing group. A related argument by Wydick (1996) shows that once sufficiently strong and credible threats of social sanctions against a defaulting group member exist, group lending will be able to deter moral hazard. In the empirical analysis, a similar, but not identical structure used by Wydick (1999) is utilized to measure group pressure among group members. Group pressure *Pressure* is measured by utilizing five yes/no questions asked to group leaders: whether group members are willing to practice pressure against another group member late in repaying, whether the group feels that practicing such pressure is difficult, whether group members feel moral to repay group loan, whether group members repay to stay on good terms with each other, and whether the group has an internal code to punish a defaulting group member. *Pressure* is thus an index equal to the number of yes responses to these questions.

In Ahlin and Townsend (2005) modification of Stiglitz (1990), BBG (1994) and BC (1995) showed that these models contain predictions on the effect of cooperation on repayment
rates. Cooperation in Stiglitz’s model enables the group to jointly choose the type of project. This in turn circumvents free-riding of one member on his partner’s safe behavior which improves repayment. In BBG model, group members who prefer safe behavior in non-cooperative groups will be willing to exert cheap penalties on other members who prefer risky behavior while cooperative groups will not be willing to do so. Cooperation in BBG model therefore reduces repayment. As in BBG, BC model predicts that cooperation decreases repayment. When groups behave cooperatively, borrowers commit ex ante not to use penalties against borrower $i$ if borrower $i$’s cost of repaying exceeds borrower $j$’s benefit from a non-delinquent $i$, and vice versa. When groups behave non-cooperatively, groups cannot commit not to impose penalties, and the borrower who realizes higher output will use penalties against a low output borrower to force repayment ex post even if the cost to the low output borrower is higher than the benefit to the high output borrower. In the empirical analysis, a similar, but not identical, structure by Ahlin and Townsend is utilized to measure cooperation among group members. Our measure of cooperation utilizes 6 yes/no questions asked to group leaders; whether cooperation to choose the place of business, referring customers to other group members, helping with free labor, helping with money, cooperation to purchase inputs, cooperation to sell output has occurred during the current cycle of lending. The index is the number of yes responses to these six questions. The same set of questions was asked twice regarding non-related and related group members respectively. $Coop1$ therefore measures cooperation among non-relatives and $Coop2$ measures cooperation among relatives within groups.

**Social Ties Variables**

Floro and Yotopolous (1991) showed that the success of group lending depends on its ability to harness social ties among borrowers to improve loan repayment. The importance of
social ties is explained in terms of the consequences of a group member default. Since default has a negative impact on other group members’ returns and future access to loans, and since borrowers are sensitive to their existing social network, borrowers will lessen their moral hazard behavior. Consequently, social ties between group members improve the group repayment performance. Our measure of social ties Socialties utilizes 6 yes/no questions asked to group leaders; whether she can get any type of help from other group members if needed, whether she can count on other group members to take care of her child if she is in need to go away for awhile, whether she has visited group members in the past week, whether she has had phone conversations with other group members in the past week, whether she seeks help from other group members to make a decision, whether she seeks mediation from others to solve a dispute with other group members. Socialties thus is an index equal to the number of yes responses to these six questions.

5. Empirical Results

The following empirical analysis uses heteroscedastic probit and negative binomial models to estimate the effects of a number of independent variables on group repayment performance, Delinquency and Delinquency Intensity. Our main hypotheses to be tested are the effect of screening, monitoring, group pressure, and social ties on groups’ repayment performance.

We start by estimating a base model that includes our measures of screening, monitoring, group pressure, social ties and other control variables including repayment history, loan size, outside credit availability, and education.

We then consequently add variables that may influence a group’s repayment performance: a dummy variable to capture any difference in repayment behavior across the two branches
surveyed, the mean size of land owned by the group, groups’ religion intensity, and the number of years since a group took its first loan.

5.1. Probit Results

The following empirical analysis uses a heteroscedastic probit model to estimate the effects of a number of independent variables on group repayment performance, Delinquency.

The importance of using the heteroscedastic probit model as opposed to probit model is stressed in Greene (2000, p. 828): “If the disturbances in the underlying regression are heteroscedastic, then the maximum likelihood estimators are inconsistent and the covariance matrix is inappropriate. This result is particularly troubling because the probit model is most often used with microeconomic data, which are frequently heteroscedastic.” In the simple probit model, the error term is normalized to have a variance of one. The heteroscedastic probit model introduces heteroscedasticity of the error term of the dependent variable in the simple probit model. In doing so, we allow the error term to vary according to the general formulation analyzed by Harvey (1976),

\[ \text{Var}(e_i) = \sigma_i^2 = \left( \exp(z \gamma) \right)^2 \]  

where \( z \) is a vector of variables that includes one or more of the independent variables and \( \gamma \) is a vector of coefficients. Denoting delinquency by \( y = 1 \) and no delinquency by \( y = 0 \), we model the probability of delinquency by a heteroscedastic probit model:

\[
\text{Pr}(y = 1) = \Phi \left( \frac{x \beta}{\exp(z \gamma)} \right)
\]

\[
\text{Pr}(y = 0) = 1 - \Phi \left( \frac{x \beta}{\exp(z \gamma)} \right)
\]  

(2)
where $\Phi$ is the normal distribution function, $x$ is a vector of independent variables, and $\beta$ is a vector of parameters. Maximum likelihood estimation of $\beta$ and $\gamma$ allows us to perform a likelihood ratio test for the hypothesis that $\gamma = 0$, a condition that corresponds to homoscedastic errors.\footnote{For an application of this test, see Knapp and Seaks (1992).} Equation 2 is estimated with $z$ defined to contain outside credit availability, $C_{\text{option}}$.

Heteroscedastic probit results are shown in Table 3. The likelihood ratio tests reported at the bottom of the table and the t-values of the null hypothesis that $\gamma = 0$ reject any model without heteroscedasticity.

Since the dependent variable involves late repayment at any time during the current loan cycle, then groups with longer history are more likely to have late repayment. From the baseline model, Model 1, the coefficient on $\ln\text{rephist}$, the natural log of repayment history, is positive as expected and statistically significant. Groups with longer history of repayment have higher probability of late repayment. This probability increases at a decreasing rate as shown by the positive sign on the coefficient of $\ln\text{rephist}$.

The signs on the loan size in our model suggest an inverted U relationship of delinquency with loan size.\footnote{Recall that our repayment measure is a dummy $= 1$ if a group had at least one late repayment and zero otherwise.} Statistically, the coefficients on $\text{loansize}$ and $\text{loansizesq}$ are significant at 10% level.\footnote{Loansize can be endogenous. Lenders usually increase loan size over time to those groups with good past performance. We tested all models for endogeneity using the Smith-Blundell (1986) method using the percentage of new members in a group as an instrumental variable for the loan size. Endogeneity of the loans size was rejected in all models. The exogeneity of the loan size is not surprising given the dynamic incentives followed by the MFW and the structure of the borrowing groups. Group members are allowed to switch to their preferred groups at the beginning of each loan cycle and new borrowers may join old groups. New members start with small loan size of JD 200 and can go up to JD 500 over time. Therefore, old good performing groups may not be associated with total larger group loans if there are new members joining these groups. For example, a group of four in their, say, fifth loan cycle, may have a total loan size of JD 800.} Our empirical results on loan size go in line with Sharma and Zeller (1996) finding but are contrary to what was found in Ahlin and Townsend (2005) and Godquin (2002).\footnote{Our empirical results on loan size go in line with Sharma and Zeller (1996) finding but are contrary to what was found in Ahlin and Townsend (2005) and Godquin (2002).}
In the Stiglitz (1990) model and in the Ahlin and Townsend extended model of BBG (1994), risky projects become relatively more attractive as loan size increases which enforces unwilling delinquency to increase. While our results show evidence of this effect, they also show that a further increase in loan size reduces delinquency. A further increase in loan size of a group will also increase that group’s joint liability in case of default. Group members will therefore have more incentive to monitor each other and apply more group pressure on those members who show bad signs of repayment behavior. More monitoring and group pressure are expected to improve the repayment behavior of the individual group members.

In Model 5, after controlling for branch, land, religion, and group age, LoanSize and LoanSize$^2$ become statistically insignificant.

Projects returns and therefore repayment are expected to be positively influenced by the productivity of the group. Our measure of Productivity, Education, is a dummy variable that is equal to 1 if a group has an average educational attainment of 4 or above. Surprisingly, Education is insignificant in all models but the last one. In Model 5, after controlling for branch, land, religion, and group age, Education still unexpectedly positive. That is, groups with high level of education have higher probability of late repayment relative to those of low education.\textsuperscript{15} The empirical literature on the effect of education on repayment found mixed results. Ahlin and Townsend (2005) found that more productive groups, in terms of education, have better repayment performance. Zeller (1998) using literacy as a measure of human capital found that the coefficient on literacy is not statistically different from zero.

\textsuperscript{15} Different measures of productivity like the mean and median of groups’ educational attainment yielded similar results.
Godquin (2002) found that education worsens repayment in the whole sample but has no effect on the split samples.

An explanation of this may lie on the fact that the highly educated groups are less credit rationed. The MFW typically begins by lending groups small amounts and then increasing loan size for these groups with satisfactory repayment. If a group faces a high degree of credit rationing it implies that this group has unfulfilled credit demand. In the survey, almost 96% of the group leaders expressed their willingness to borrow larger loans at the current interest rate. In order to protect future larger loans, groups with higher unfulfilled credit demand will be expected to increase their efforts to improve repayment performance. In the survey, we asked the group leaders about their desired loan sizes. We also have the group leaders’ actual loan sizes from the MFW’s data base. These data allows us to measure the degree of credit rationing of the group leaders by taking the difference between the desired loan sizes and the actual ones expressed as a percent of the desired loan sizes. Assuming that the group leader and his partners are identically credit rationed, we found a negative and significant correlation between Education and credit rationing of -0.19 at the 1% level. That is, highly educated groups are associated with lower degree of credit rationing. Since these groups face lower unfulfilled credit demand and less concerned about future larger loans, they are expected to exert less effort to improve their repayment performance.

Both Stiglitz (1991) and BBG (1994) have predictions on the effect of outside borrowing options on repayment rates; groups with more outside borrowing options will experience higher loan size giving group members greater incentive for risky projects. The sign on Cropption is as expected by theory but statistically insignificant under all specifications.

The practice of screening is expected to crowd in safer type of borrowers which should improve repayment. The signs on the screening variables are negative as expected; screening
reduces delinquency. While Screen has the expected sign in all models, it is not a significant predictor of late repayment. In adverse selection models and as a prerequisite for screening to take place, borrowers were assumed to know each other type. In all models, the sign on Knowtype is negative as expected and statistically significant. Borrowers’ knowledge about the quality and sales of each other occupations improves their group repayment performance. Similar results of the positive effect of screening on good repayment are also documented in Wenner (1995) and Sharma and Zeller (1996).

With group lending, individual borrowers are liable for themselves and for others in their group, therefore, they have incentives to monitor each others’ actions. The signs of the coefficients on cost of monitoring measures are all negative as expected. More monitoring mitigates moral hazard and leads to lower delinquency. However, occupational homogeneity, samebus, and the percentage of group members with access to phone services, Phone, are not significant predictors of delinquency in all probit models. A similar measure of occupational homogeneity used by Ahlin and Townsend (2005) was also found to be a poor predictor of repayment. Relative, measures the percentage of members in the group that are related to each other. The sign on the coefficient of Relative is negative and statistically significant under all specifications. Since the ease of information flow, and therefore monitoring, is expected to be better among relatives, there would be less moral hazard and consequently lower delinquency. Ahlin and Townsend (2005) and Sharma and Zeller (1996) used similar measures to Relative. In these papers, however, the percentage of relatives on a group worsens repayment performance. Both papers argue that it is difficult to impose penalties on relatives which weaken the repayment enforcement process. Contrary to these papers, our

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16 Occupational homogeneity in Ahlin and Townsend was used as a measure of output correlation. The authors indicate that this measure can be used as a monitoring proxy.
results suggest that any difficulty in imposing penalties on relatives is overcome by the greater ease of monitoring relatives’ actions.

Exercising pressure and imposing penalties against defaulting members mitigate moral hazard while cooperation among group members may dilute the willingness to exercise pressure and the imposition of penalties which encourages moral hazard. The signs of the coefficients on all group pressure measures give an evidence of this statement. In all models, the sign on *Pressure* is negative and statistically significant indicating the importance of group pressure in alleviating moral hazard behavior of the borrowers. Similar results were found by Ahlin and Townsend (2005) and Wydick (1999). The signs on the cooperation measures are positive indicating that a greater degree of cooperation among group members increases the probability of delinquency. The signs and significance levels of cooperation measures are the same in all models. Cooperation among non-relatives, *Coop1*, does not seem to be a strong predictor of delinquency as it is statistically insignificant. Cooperation among relatives, *Coop2*, however, has a strong positive predictive power on delinquency.

The importance of social ties on repayment is explained in terms of the consequences of a group member’s default. Since default has a negative impact on other group members’ returns and future access to loans, and assuming that borrowers are sensitive to their existing social network, borrowers will lessen their moral hazard behavior. As expected, our measure of social ties, *Socialties*, shows a negative and strong impact on delinquency in all models. Our finding of the effect of *Socialties* on repayment is contrary to Godquin (2002) results but in line with Zeller (1998). *Relative*, which can be viewed as a measure of social ties, goes in line with our finding that social ties reduces the probability of delinquency.

In Models 2 through 5, we add new variables that are usually included in the empirical and theoretical literature on the determinants of delinquency. In Model 2, we try to capture any
difference in repayment behavior of group borrowers across the two branches surveyed. The sign on \textit{Branch}, which is a dummy variable equals to one if a group belongs to Al-Rusaifa’s branch, hold a negative sign in models 2 through 5. While the negative sign suggests that groups that belong to Al-Rusaifa’s branch have lower probability of delinquency, such probability is statistically insignificant.

In Model 3, we include \textit{Land}, the mean size of land owned by a group. The sign on \textit{Land} is negative as expected. Assets ownership improves the capacity of the groups to meet repayment requirements on time. However, this effect is statistically insignificant in Models 3 through 5.

Next we include a measure of a cultural factor that may affect group repayment performance, \textit{Religion}. In this model as well as in model 5, \textit{Religion} is statistically insignificant.

In Model 5, we include the group age, \textit{Groupage}, the number of years since the group took its first loan. The sign and the statistical significance of \textit{Groupage} suggest that groups may envision their relationship with the lending institution as transitory and therefore exert lower effort to repay on time on later loan cycles. In this model, \textit{loansize} and \textit{loansizesq} have the same signs as in the previous model, but the inclusion of \textit{Groupage} renders them insignificant.

5.2. Negative Binomial Results

The following empirical analysis uses Negative Binomial estimation to test the effects of a number of independent variables on group repayment performance, \textit{Delinquency Intensity}. The negative binomial model derives from a poisson distribution. The poisson has been suggested as the benchmark model for count data (Cameron and Trevedi 1998). In the poisson model $y_i$ has mean $\mu_i = \exp(x_i'\beta)$ and variance $\mu_i$, equaldispersion. That is;

$$\mu_i = E(y_i | x_i) = \text{var}(y_i | x_i) = \exp(x_i'\beta)$$ (3)
However, the conditional variance in most applications is greater than the conditional mean. While such overdispersion does not affect the poisson regression model estimates being consistent, such estimates are inefficient. The standard errors of the poisson regression model will be biased downward which will over estimate the significance of the explanatory variables (Long 1997).

Overdispersion seems likely in our study because there are important explanatory variables that are difficult to capture (e.g., group members’ income, group members’ occupation risk level), and because error may exist in the estimates of some variables (pure randomness).

*Delinquency Intensity* ranges in values between zero and 41. Approximately 85% of the sample takes values of 0, 1, 2, 3, or 4. The mean of the number of days of late repayment is 3.1 days with a variance of 40.26. The raw data are therefore overdispersed and the inclusion of the regressors did not eliminate this overdispersion in Poisson regression model indicating its inadequacy of fit. If overdispersion exists, a Poisson model is not appropriate and a negative binomial model can be used instead.

A negative binomial regression model includes a random error term $\varepsilon_i$ representing the effect of omitted explanatory variables or pure randomness. Therefore, equation 3 can be written as:

$$
\hat{\mu}_i = \exp\left( x_i \beta + \varepsilon_i \right) = \mu_i \exp(\varepsilon_i) \quad (4)
$$

where $\exp(\varepsilon_i)$ is a gamma distributed random variable with mean one and variance $\alpha$.

The negative binomial probability distribution is a mixture of poisson distribution that allows the poisson mean to be gamma distributed. The negative binomial distribution is given by:
\[
\Pr(y_i | x_i) = \frac{y_i!}{y_i! \Gamma(\alpha^{-1})} \left( \frac{\alpha^{-1}}{\alpha^{-1} + \mu_i} \right)^{\alpha} \left( \frac{\mu_i}{\alpha^{-1} + \mu_i} \right)^{y_i}, \alpha > 0
\]  

(5)

where \( \Gamma \) is the gamma function. Equation 5 has a mean \( \mu_i \) and variance

\[
\text{var}(y_i | x_i) = \mu_i + \alpha \mu_i^2
\]  

(6)

where \( \alpha \), the variance of the gamma-distributed error, is the overdispersion parameter.

If \( \alpha = 0 \), the negative binomial reduces to the Poisson distribution. The appropriateness of applying the Poisson model versus the negative binomial model can be assessed based on the statistical significance of estimate value of \( \alpha \).

We run similar models to those in Table 3. Models 6 through 10 correspond to Models 1 through 5 in Table 3 but with a different dependent variable. The dependent variable in the following analysis is the number of days late of repayment. Using the heteroscedasticity-robust standard errors, the negative binomial results are shown in Table 4.

Table 4 shows that there is a strong evidence of overdispersion. The dispersion parameter is positive and significant at the 1% level in all models. Alternatively, the computed likelihood ratio tests of overdispersion are even more highly significant.

Similar to the probit estimations, the negative binomial estimations show that the coefficient on \( \lnrephist \) is positive and statistically significant. That is, the longer the history of repayment, the more days of late repayments.

The signs on the loan size in our model suggest an inverted U relationship of delinquency with loan size. Statistically, the coefficients on \( \text{loansize} \) and \( \text{loansizesq} \) are significant at 1% level in all models. Due to possible endogeneity in loan size in the negative binomial model, we give no interpretation on the effect of loan size on the number of days of late repayment.\(^{17}\)

\(^{17}\) Testing for endogeneity in negative binomial model is to be done later.
Under all models’ specifications, *Education* has an unexpected sign. That is, groups with higher level of education have more days of late repayment. As mentioned previously, highly educated group face lower credit constraints and are less concerned about future larger loans which give them less motivation to improve their repayment performance. The negative effect of education on good repayment has not been documented before. Ahlin and Townsend (2005) found that more productive groups, in terms of education, have better repayment performance. Zeller (1998) using literacy as a measure of human capital found that the coefficient on literacy is not statistically different from zero.

While the availability of outside borrowing options, *Croptions*, performs poorly in probit models, it gains predictive power in the negative binomial models with the positive expected sign. Groups with more outside borrowing opportunities experience higher loan size giving group members greater incentives for riskier projects and consequently more days of late repayment. One may also argue that groups with more alternative credit sources may value the MFW’s services less which leads to more days of late repayment (Wenner (1995)).

The signs on the screening variables are negative as expected but lose predictive power in models 6 and 7. In models 8 through 10, and after the consequent inclusion of land, religion, and group age, *Knowtype* turns significant at standard significance levels while *Screen* remains insignificant. Borrowers’ knowledge about the quality and sales of each others’ occupations seems to matter in reducing the number of days of late repayment.

The performance of monitoring measures changes in the negative binomial models compared to the probit models. The sign on *Samebus* holds an unexpected sign in models 8 through 10 but it is statistically insignificant, the performance of *Relative* is comparable to those in probit models, *Phone* has the expected sign but has no predictive power. Having
more relatives in a group eases the process of monitoring and reduces the number of late repayment days.

All the group pressure measures have the expected signs and have significant explanatory power on the number of days of late repayment in all the negative binomial models. The results show that a greater degree of Pressure among group members reduces the number of days of late repayment. Cooperation among relatives and non-relatives increases the number of days of late repayment. Cooperation among group members seems to dilute the willingness to exercise pressure on delinquent members which encourages late repayment. Cooperation among non-relatives enters with the same sign but significantly in the negative binomial models compare to those in probit models.

Ahlin and Townsend (2005) found that cooperation among non-relatives affects repayment worsens. Our results show that cooperation, whether it is among relatives or non-relatives, worsens repayment.

Similar to probit models, Socialties shows a negative and significant impact on delinquency intensity in all the negative binomial models. The effect of Relative on repayment goes in line with the effect of Socialties. Group members’ sensitivity to their social network lessens their moral hazard behavior and consequently improves their repayment performance.

In Models 7 through 10 we add the rest of the control variables; namely, Branch, Land, Religion, and Groupage respectively.

In models 7 through 10, the sign on Branch, which is a dummy variable equal to one if a group belongs to Al-Rusaifa’s branch, hold a negative sign. Unlike the probit models, Branch in the negative binomial models is statistically significant. The negative sign suggests that groups that belong to Al-Rusaifa’s branch have fewer days of late repayment.
Next we include $Land$, the mean size of land owned by a group. The sign on $Land$ is negative as expected and statistically significant in models 8 through 10. Assets ownership improves the capacity of the groups and reduces the number of days of late repayment.

While the cultural factor in probit model, $Religion$, holds a positive sign with negligible predictive power, it holds a negative sign and is statistically significant in the negative binomial models. $Religion$ seems to not affect the occurrence of late repayment, but once a late repayment occurs, more religious groups repay faster.

In Model 10, we include the group age, $Groupage$. While the sign on $Groupage$ is still positive as in probit model, it loses its predictive power. Other results are robust to the inclusion of $Groupage$.

6. Conclusion

This paper empirically tests the theoretical predictions about repayment performance in group lending programs. We use data from a survey of 160 MFW borrowing groups to test the significance of screening, monitoring, group pressure, and social ties on borrowing group behavior in terms of repayment performance. Our results are consistent with the vast majority of the theoretical group lending models.

Though not overwhelmingly manifested, the results show that screening plays a role in reducing delinquency. Group members that have better knowledge about each other occupation quality tend to reduce delinquency.

Our unmatched rich data on group pressure reveals its significance impact in reducing delinquency. All group pressure variables hold the expected signs and two out of three variables show negative impact on delinquency in all models. With the exception of Ahlin
and Townsend (2005), this result has not been documented in the previous empirical literature.

Next the percentage of relatives in a group showed a significant negative impact on delinquency. In contrast, the previous empirical literature found that relatives have a negative impact on repayment. Relatives may allow for better communication but may be harder to impose sanctions against. Our results support the hypothesis that more relatives in a group ease the process of monitoring and this reduces moral hazard.

The analysis shows that groups with higher level of social ties have a lower delinquency. This is one of the central findings of this paper. What enhances this result is the negative effect of the percentage of relatives in a group on delinquency, given that such a measure can also be used as an indicator of social ties. Except for Zeller (1998), this result is consistent with theory but contrary to the previous empirical literature.

We also found that loan and socio-economics characteristics have to be taken into consideration for an effective understanding of the determinants of the groups’ repayment behavior. The loan size showed a non-linear effect on delinquency. While increasing loan size deepens delinquency, a further increase dampens it. Surprisingly, we find that education has a positive effect on delinquency. Another interesting finding is the fact that the access to more outside credit and group age increase delinquency while asset ownership seems to enhance the groups’ ability to repay on time. We find that religious beliefs affect the intensity of delinquency, with more religious borrowers repaying quicker in case of delinquency.

The conclusion of this research suggests that the performance of group lending as an institution is more likely to be more successful if group members screen and monitor each other, impose greater social pressure and have strong social ties.
References


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### Table 1
A Description of Group Loans at the MFW

<table>
<thead>
<tr>
<th>Loan Type</th>
<th>Group Loans</th>
</tr>
</thead>
<tbody>
<tr>
<td>Creation Date</td>
<td>1996</td>
</tr>
<tr>
<td>Client Type</td>
<td>Urban</td>
</tr>
<tr>
<td>Collateral Requirements</td>
<td>Group guarantee</td>
</tr>
<tr>
<td>Repayment Schedule</td>
<td>Bi-weekly, monthly</td>
</tr>
<tr>
<td>Nominal annualized interest rate (first loan)</td>
<td>21% flat</td>
</tr>
<tr>
<td>Additional Fees (JD)</td>
<td>5</td>
</tr>
<tr>
<td>Loan Size Range (JD)</td>
<td>200-500</td>
</tr>
<tr>
<td>Average Loan Size (JD)</td>
<td>320</td>
</tr>
<tr>
<td>Loan Term range</td>
<td>28 weeks, 8 months</td>
</tr>
</tbody>
</table>
### Table 2
Variables Descriptive Statistics

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
<th>Mean</th>
<th>St. Dev</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Dependent Variables</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Delinquency</td>
<td>Dummy = 1 if the group had at least one late repayment up to time of survey</td>
<td>0.525</td>
<td>0.500</td>
</tr>
<tr>
<td>Delinquency Intensity</td>
<td>Number of days of late repayment by the group up to time of survey</td>
<td>3.106</td>
<td>6.345</td>
</tr>
<tr>
<td><strong>Control Variables</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Rephist</td>
<td>Number of repayments made or supposed to be made by the group during the current loan cycle</td>
<td>5.962</td>
<td>2.479</td>
</tr>
<tr>
<td>Loansize</td>
<td>Group loan size in hundreds of JD</td>
<td>15.76</td>
<td>4.19</td>
</tr>
<tr>
<td>Education</td>
<td>Dummy = 1 if the group has an average education of 4 and above</td>
<td>0.112</td>
<td>0.316</td>
</tr>
<tr>
<td>Branch</td>
<td>Dummy = 1 if the group belongs to Al-Rusaifa Branch</td>
<td>0.475</td>
<td>0.500</td>
</tr>
<tr>
<td>Land</td>
<td>The mean of the size of land owned by the group measured in hundreds of square meters</td>
<td>4.304</td>
<td>10.569</td>
</tr>
<tr>
<td>Religion</td>
<td>Percentage of groups who pray five times a day</td>
<td>0.867</td>
<td>0.215</td>
</tr>
<tr>
<td>Groupage</td>
<td>Number of years since the group took its first loan</td>
<td>4.037</td>
<td>2.571</td>
</tr>
<tr>
<td><strong>Outside Credit</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Croption</td>
<td>Percentage of members with access to credit from individual outside the group</td>
<td>0.246</td>
<td>0.348</td>
</tr>
<tr>
<td><strong>Screening</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Screen</td>
<td>Dummy = 1 if the group members rejected a borrower who would like to join them</td>
<td>0.568</td>
<td>0.496</td>
</tr>
<tr>
<td>Knowtype</td>
<td>Dummy = 1 if the group members know the quality of each others’ work</td>
<td>0.950</td>
<td>0.218</td>
</tr>
<tr>
<td><strong>Monitoring</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Samebus</td>
<td>The Probability that two members have same occupation</td>
<td>0.156</td>
<td>0.175</td>
</tr>
<tr>
<td>Relative</td>
<td>Percentage of relatives in groups</td>
<td>0.227</td>
<td>0.294</td>
</tr>
<tr>
<td>Phone</td>
<td>The percentage of group members with access to either land or cell phone services.</td>
<td>0.646</td>
<td>0.344</td>
</tr>
<tr>
<td><strong>Group Pressure</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pressure</td>
<td>An index of group pressure from 0 to 5</td>
<td>3.881</td>
<td>0.856</td>
</tr>
<tr>
<td>Coop1</td>
<td>An Index of cooperation between non-relatives from 0 to 6</td>
<td>3.193</td>
<td>1.348</td>
</tr>
<tr>
<td>Coop2</td>
<td>An Index of cooperation between relatives from 0 to 6</td>
<td>1.356</td>
<td>1.816</td>
</tr>
<tr>
<td><strong>Social ties</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Socialties</td>
<td>An index of social ties from 0 to 6</td>
<td>5.381</td>
<td>1.273</td>
</tr>
</tbody>
</table>
### Table 3
Heteroscedastic Probit Regression Results

**Delinquency** = 1 if a group had at least one late repayment and zero if a group paid all installments on time.

Numbers in Parentheses are t-values
Significance level of 10, 5 and 1% are denoted by *, **, *** respectively

<table>
<thead>
<tr>
<th>Variable</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
<th>Model 5</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Constant</strong></td>
<td>-0.377 (-0.16)</td>
<td>-0.180 (-0.08)</td>
<td>-0.271 (-0.11)</td>
<td>-0.622 (-0.24)</td>
<td>-0.494 (-0.18)</td>
</tr>
<tr>
<td><strong>Control</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lnrephist</td>
<td>4.712 (4.42)***</td>
<td>5.112 (4.33)***</td>
<td>5.130 (4.22)***</td>
<td>5.207 (4.14)***</td>
<td>5.840 (3.92)***</td>
</tr>
<tr>
<td>Loansize</td>
<td>0.448 (1.68)*</td>
<td>0.446 (1.64)*</td>
<td>0.451 (1.65)*</td>
<td>0.446 (1.63)*</td>
<td>0.381 (1.31)</td>
</tr>
<tr>
<td>Loansizesq</td>
<td>-0.013 (-1.72)*</td>
<td>-0.013 (-1.66)*</td>
<td>-0.012 (-1.65)*</td>
<td>-0.012 (-1.63)*</td>
<td>-0.012 (-1.45)</td>
</tr>
<tr>
<td>Education</td>
<td>0.729 (1.23)</td>
<td>0.747 (1.22)</td>
<td>0.989 (1.42)</td>
<td>0.982 (1.40)</td>
<td>1.224 (1.67)*</td>
</tr>
<tr>
<td>Branch</td>
<td>-0.419 (-1.15)</td>
<td>-0.466 (-1.26)</td>
<td>-0.467 (-1.25)</td>
<td>-0.619 (-1.50)</td>
<td></td>
</tr>
<tr>
<td>Land</td>
<td>-0.028 (-0.90)</td>
<td>-0.026 (-0.85)</td>
<td>-0.035 (-1.00)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Religion</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Groupage</td>
<td></td>
<td>0.332 (0.36)</td>
<td>0.649 (0.65)</td>
<td>0.135 (1.71)*</td>
<td></td>
</tr>
<tr>
<td><strong>Outside Credit</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Croption</td>
<td>0.695 (0.89)</td>
<td>0.828 (0.96)</td>
<td>0.944 (1.05)</td>
<td>0.972 (1.05)</td>
<td>1.163 (1.05)</td>
</tr>
<tr>
<td><strong>Screening</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Screen</td>
<td>-0.359 (-1.13)</td>
<td>-0.441 (-1.31)</td>
<td>-0.426 (-1.26)</td>
<td>-0.448 (-1.29)</td>
<td>-0.561 (-1.49)</td>
</tr>
<tr>
<td>Knowtype</td>
<td>-1.509 (-1.96)**</td>
<td>-1.405 (-1.81)*</td>
<td>-1.424 (-1.81)*</td>
<td>-1.429 (-1.81)*</td>
<td>-1.557 (-1.89)*</td>
</tr>
<tr>
<td><strong>Monitoring</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Samebus</td>
<td>-0.661 (-0.79)</td>
<td>-0.589 (-0.69)</td>
<td>-0.580 (-0.68)</td>
<td>-0.607 (-0.70)</td>
<td>-0.517 (-0.58)</td>
</tr>
<tr>
<td>Relative</td>
<td>-3.724 (2.78)***</td>
<td>-3.934 (2.84)***</td>
<td>-3.900 (2.78)***</td>
<td>-3.909 (2.79)***</td>
<td>-4.379 (2.94)***</td>
</tr>
<tr>
<td>Cphone</td>
<td>-0.634 (-1.04)</td>
<td>-0.554 (-0.87)</td>
<td>-0.604 (-0.94)</td>
<td>-0.568 (-0.87)</td>
<td>-0.509 (-0.74)</td>
</tr>
<tr>
<td><strong>Group Pressure</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pressure</td>
<td>-0.439 (-2.32)***</td>
<td>-0.506 (-2.48)***</td>
<td>-0.480 (-2.35)***</td>
<td>-0.462 (-2.21)**</td>
<td>-0.546 (-2.46)***</td>
</tr>
<tr>
<td>Coop1</td>
<td>0.010 (0.07)</td>
<td>-0.002 (-0.02)</td>
<td>0.024 (0.16)</td>
<td>0.015 (0.10)</td>
<td>0.050 (0.31)</td>
</tr>
<tr>
<td>Coop2</td>
<td>0.655 (3.15)***</td>
<td>0.678 (3.15)***</td>
<td>0.686 (3.14)***</td>
<td>0.694 (3.16)***</td>
<td>0.771 (3.31)***</td>
</tr>
<tr>
<td><strong>Social ties</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Socialites</td>
<td>-0.540 (-3.28)***</td>
<td>-0.558 (-3.25)***</td>
<td>-0.580 (-3.31)***</td>
<td>-0.581 (-3.32)**</td>
<td>-0.613 (-3.33)***</td>
</tr>
<tr>
<td>Log Likelihood</td>
<td>-71.0556</td>
<td>-70.3609</td>
<td>-69.9016</td>
<td>-69.8345</td>
<td>-68.2130</td>
</tr>
<tr>
<td><strong>Insigma2</strong></td>
<td></td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Croption (γ)</td>
<td>1.247 (2.43)***</td>
<td>1.406 (2.61)***</td>
<td>1.433 (2.63)***</td>
<td>1.470 (2.60)***</td>
<td>1.731 (2.65)***</td>
</tr>
<tr>
<td>Likelihood-ratio test of Insigma2=0</td>
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</tr>
<tr>
<td>Chi2(1)</td>
<td>8.09</td>
<td>9.46</td>
<td>9.80</td>
<td>9.94</td>
<td>11.96</td>
</tr>
<tr>
<td>p-value</td>
<td>0.0045</td>
<td>0.0021</td>
<td>0.0017</td>
<td>0.0016</td>
<td>0.0005</td>
</tr>
</tbody>
</table>
### Table 4

**Negative Binomial Results**

*Delinquency Intensity:* The number of late days of repayment

Numbers in Parentheses are t-values

Significance level of 10, 5 and 1% are denoted by *, **, *** respectively

<table>
<thead>
<tr>
<th>Variable</th>
<th>Model 6</th>
<th>Model 7</th>
<th>Model 8</th>
<th>Model 9</th>
<th>Model 10</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Constant</strong></td>
<td>-4.517 (-2.34)**</td>
<td>-4.395 (-2.49)**</td>
<td>-3.950 (-2.37)**</td>
<td>-2.874 (-1.74)*</td>
<td>-3.070 (-1.81)*</td>
</tr>
<tr>
<td><strong>Control</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Loansize</td>
<td>0.782 (3.51)***</td>
<td>0.795 (3.63)***</td>
<td>0.759 (3.66)***</td>
<td>0.707 (3.47)***</td>
<td>0.741 (3.51)***</td>
</tr>
<tr>
<td>Loansizesq</td>
<td>-0.025 (-3.89)***</td>
<td>-0.025 (-4.02)***</td>
<td>-0.024 (-4.06)***</td>
<td>-0.022 (-3.83)***</td>
<td>-0.023 (-3.91)***</td>
</tr>
<tr>
<td>Education</td>
<td>0.642 (1.93)**</td>
<td>0.557 (1.68)*</td>
<td>0.815 (2.46)***</td>
<td>0.856 (2.63)***</td>
<td>0.703 (2.77)***</td>
</tr>
<tr>
<td>Branch</td>
<td>-0.509 (-1.73)*</td>
<td>-0.606 (-1.95)**</td>
<td>-0.668 (-2.16)**</td>
<td>-0.703 (-2.30)**</td>
<td></td>
</tr>
<tr>
<td>Land</td>
<td>-0.022 (-1.79)*</td>
<td>-0.022 (-1.91)**</td>
<td>-0.024 (-2.12)**</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Religion</td>
<td>-0.871 (-2.31)**</td>
<td>-0.827 (-2.15)**</td>
<td></td>
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<td></td>
</tr>
<tr>
<td>Groupage</td>
<td></td>
<td></td>
<td></td>
<td>0.064 (1.36)</td>
<td></td>
</tr>
<tr>
<td><strong>Outside Credit</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cروption</td>
<td>0.644 (1.97)**</td>
<td>0.827 (2.35)***</td>
<td>-0.912 (2.58)**</td>
<td>0.823 (2.34)***</td>
<td>0.760 (2.13)***</td>
</tr>
<tr>
<td><strong>Monitoring</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Samebus</td>
<td>-0.046 (-0.08)</td>
<td>-0.052 (-0.09)</td>
<td>0.054 (0.09)</td>
<td>0.097 (0.17)</td>
<td>0.093 (0.16)</td>
</tr>
<tr>
<td>Relative</td>
<td>-2.015 (-2.45)***</td>
<td>-1.813 (-2.25)**</td>
<td>-1.647 (-1.98)**</td>
<td>-1.637 (-2.21)**</td>
<td>-1.710 (-2.25)**</td>
</tr>
<tr>
<td>Cphone</td>
<td>-0.359 (-0.80)</td>
<td>-0.373 (-0.82)</td>
<td>-0.420 (-0.93)</td>
<td>-0.523 (-1.18)</td>
<td>-0.472 (-1.12)</td>
</tr>
<tr>
<td><strong>Group Pressure</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pressure</td>
<td>-0.358 (-2.78)***</td>
<td>-0.440 (-3.51)***</td>
<td>-0.483 (-3.74)***</td>
<td>-0.477 (-3.73)***</td>
<td>-0.513 (-3.89)***</td>
</tr>
<tr>
<td>Coop1</td>
<td>0.176 (1.83)*</td>
<td>0.174 (1.84)*</td>
<td>0.222 (2.22)***</td>
<td>0.219 (2.09)**</td>
<td>0.223 (2.16)**</td>
</tr>
<tr>
<td>Coop2</td>
<td>0.297 (2.38)***</td>
<td>0.255 (2.04)**</td>
<td>0.260 (2.06)**</td>
<td>0.223 (1.95)**</td>
<td>0.243 (2.06)**</td>
</tr>
<tr>
<td><strong>Social ties</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Socialites</td>
<td>-0.437 (-3.92)***</td>
<td>-0.408 (-3.76)***</td>
<td>-0.418 (-4.00)***</td>
<td>-0.389 (-3.65)***</td>
<td>-0.411 (-3.64)***</td>
</tr>
<tr>
<td><strong>Screening</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Screen</td>
<td>-0.003 (-0.02)</td>
<td>-0.079 (-0.33)</td>
<td>-0.055 (-0.23)</td>
<td>-0.026 (-0.12)</td>
<td>-0.015 (-0.07)</td>
</tr>
<tr>
<td>Knowtype</td>
<td>-1.103 (-1.59)</td>
<td>-1.093 (-1.56)</td>
<td>-1.256 (-1.77)*</td>
<td>-1.144 (-1.61)*</td>
<td>-1.159 (-1.77)*</td>
</tr>
<tr>
<td>Log Likelihood</td>
<td>-277.5303</td>
<td>-275.7614</td>
<td>-274.7269</td>
<td>-273.4404</td>
<td>-272.5573</td>
</tr>
<tr>
<td>( \alpha )</td>
<td>1.255 (5.22)***</td>
<td>1.216 (5.35)***</td>
<td>1.198 (5.57)***</td>
<td>1.125 (5.02)***</td>
<td>1.102 (4.96)***</td>
</tr>
</tbody>
</table>

Likelihood-ratio test of \( \alpha = 0 \)

| Chibar2(1) | 251.98 | 253.11 | 255.12 | 199.20 | 198.58 |
| p-value    | 0.000  | 0.000  | 0.000  | 0.000  | 0.000  |