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Enforcement in Informal Groups: The Role of Indirect Punishments on Repayment Behavior within the Financial Self-help Groups in Tanzania

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ABSTRACT

Several attempts have been made by economists to investigate the effects of negative incentives such as punishments on the propensity of members from the informal economic and social groups to repay their loans. However, the existing empirical studies have concentrated on direct punishments i.e. punishments directly related to an offence of defaulting, entirely overlooking the spillover effects of other forms of punishments (non-default related, i.e. indirect punishments) on addressing repayment problems. Differently from the existing literature, this research not only disentangles punishment into two categories i.e. direct and indirect punishments, but also applies a multilevel statistical model to assess the effects of indirect punishments on repayment performance. The results confirm not only that loan repayment behavior is influenced by indirect punishments, but indirect punishment is a proximate mechanism through which peer pressure addresses repayment problems. That is to say, punishment in other offences not related to default deters would-be defaulters from defaulting. Furthermore, indirect punishment is found to have larger effects than direct punishment in restraining individuals from defaulting. Finally, strong social ties between group members, compulsory savings and high preferences to core group services further reduce instances of defaulting.

“Altruistic punishment enhances cooperation among members of a group; People enjoy cooperating and punishing free riders; purely symbolic punishment is effective.”
Bowles and Gintis (2011)

"Humans are prone to cooperate, even with strangers; cooperation is contingent on many things; institutions matter e.g. punishes those who defects; variation in institutions is huge." Richerson, Boyd and Henrich (2003)

“Individuals interacting within rule-structured situations face choices regarding the actions and strategies they take, leading to consequences for themselves and for others; thus, understanding institutions is a serious endeavor.” Ostrom (2005)

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1.0 INTRODUCTION

"Madam, it is one hundred shilling fine for being late, the collection pot is just in front of you"

"We cannot allow her to continue missing our weekly meetings, next week we will not accepts her savings from a third person and she will pay a fine for missing the last 4 meetings"

"We will send a delegation to her house to enquire on the reason behind her late repayment, we just saw her 5 minutes ago but she is absent in this meeting where she is obliged to start repaying her debts"[1]

Which factors affect cooperation in non-firm economic institutions such as the informal financial self-help groups? This research project addresses this question by focusing on the role of punishment on repayment behavior of members of the informal financial self-help groups in Tanzania[2]. In principal, lending has always been considered as a risky activity. It is even more risky when it takes place in an informal group of people, some with limited knowledge of each other and they cannot offer any conventional physical collateral. In other words, in an economic exchange situation such as lending, between two or more individuals which is not determined by enforceable contracts, there are always material incentives to cheat the exchange partners (Fehr, Fischbacher and Gachter, 2002). For these reasons, various means have been discussed in the literature on conditions in which, lending in an informal economic group persists even in the presence of severe risks of defaulting.

Using multilevel statistical model, this study estimates the influence of both direct and indirect punishments on the probability of loan repayment. By ***indirect punishments***, I refer to penalties not related to an offence of defaulting (e.g. lateness on meeting attendance etc.)[3], while ***direct punishments*** include penalties directly related to an offence of defaulting. As this study focuses on exploring indirect punishment as a social institution that has effects beyond the offence in which it intends to address, the main guiding question is "do indirect punishments address repayment problems within the informal financial self-help groups? In other words, this study concentrates on the spillover effects of indirect punishments on repayment performance.

In the past few years developing countries including Tanzania, have embraced the idea of local collective actions (or groupings) as one of the means to economically empower vulnerable groups in the society. Proliferations of economic groups such as financial self-help groups have been widely reported in the local media revealing exceptionally high participation rates in these groups. For instance, in the span of 3 years, CARE International has facilitated the establishments of more than 2,615 groups, while ORGUT-SEDIT program

[1] These quotations are extracts from the discussions taking place inside the weekly group meetings in which were allowed to attend.

[2] In some literature these types of groups are referred to as Accumulating Savings and Credit Associations (ASCA). See Boumal (1995) for the similarities and differences between ASCA and Rotating Savings and Credit Associations (ROSCA).

[3] I use the word "indirect" because punishments referred here are not directly related to an offence of defaulting.

mobilized more than 2,000 groups around Tanzania. As these groups proliferate (with many more emerging even without external facilitation), scientific investigation is crucial to better understand the social mechanisms facilitating cooperative behavior between members. This is importantly so, because the mere presence of common interests and common expected benefits between members, are not sufficient to determine behavior in collective actions, leading to wide variations with some communities being able to generate collective goods for their members while others failing to do so (Curin, 2007). It is, therefore, important to understand the conditions working for and against sustainability of local cooperation and provision of collective good. In other words, we are asking ourselves, what factors working for or against cooperation in economic groups? This is because in the presence of higher repayment rates, the probability of groups being sustainable will be higher, and the more sustainable these groups are, the more they can contribute in improving access to credit for the majority of the poor.

There are several social mechanisms taking place within these groups. However, one of the most interesting is the prevalence of informal sanctioning mechanisms to enforce cooperative behavior. The importance of sanctioning mechanisms arise as a result of high level of informality in these groups, for instance, they are not registered with either the central or local government authorities, and therefore they cannot rely on external enforcements. Given this attribute, vast majority of empirical literature has declared the critical role of rewards and punishments in maintaining compliance to collective agreements (Boyd and Richerson 1992; Boyd and Henrich 2001; Sober and Wilson 1998). However, this group of literature has dealt primarily with the effects of direct punishment on the repayment behavior, largely ignoring the spillover effects of indirect punishments on repayment performance. The limitations in the existing literature are mainly in two areas. First, direct punishment is considered to be the only type of punishment mechanisms necessary to address repayment problems. Second, indirect punishment is ignored all together even in cases where peer pressure is explicitly discussed as one of the tool to enforce compliance. Given these limitations, this study disentangles punishments taking place within the informal financial self-help groups in order to capture the effects of each punishment category on repayment performance. The specific hypothesis to be tested is that loan repayment behavior in the informal financial self-help groups is influenced by indirect punishments, a mechanism through which peer pressure addresses repayment problems.

The rest of the paper is organized as follows. Section 2 outlines the context and the model of operations of the surveyed groups, followed by the description of the research site in Section 3. Sampling strategy and technique is described in Section 4, while Section 5 gives explanation on the survey instrument. Data from the survey are described in Section 6, while Section 7 outlines the research problem, followed by literature review in section 8. Analytical framework is discussed in Section 9 while Section 10 described an empirical model used in the study. Section 11 presents the results followed by discussion in Section 12. Section 13 concludes while Section 14 gives the limitations of the study.

2.0 CONTEXT AND THE GROUPS' OPERATIONAL MODEL

"Loans from the groups has helped in paying school fees for my children, it was really a struggle before I became a member"
"My husband was completely against these groups when I first joined, after loans from the group solved some of our family financial needs, he has joined and even allowed the weekly group meetings to be hosted at our home"

The financial self-help groups referred to in this studies have adopted different "brand" names depending on where they have generated support from. For those which have been facilitated by CARE International, they have adopted the name Village Savings and Loans Associations (VSLAs), while they are known as Village Community Banks (VICOBA) for those which have received support from a local NGO known as Social and Economic Development Initiative of Tanzania (SEDIT). There are minor differences in the way they operate and manage transactions among members.

Members of these financial self-help groups are the only customers and at the same time they are responsible for owning, managing and operating this joint financing enterprise organized on the basis of collective decision-making. The groups are characterized by a simple management structure made up of Chairperson, Secretary, Disciplinary officer and a Cashier. The group size is usually restricted to a maximum of 30 members. In some groups, members are actually made of collateral sub-groups of 5 close connected members[4]. These sub-groups have two key roles i) is to provide guarantees when one of their colleagues borrow from the group; coupled with the responsibility of peer monitoring in the case of late or default repayment ii)the sub-groups are responsible to account for the absence of their colleagues during the obligatory weekly meetings. The obligatory weekly meetings play a crucial transparency role. During these meetings; loans applications, approvals and every debtors' repayment updates are discussed openly. The groups have constitutions stipulating among other things, rules to be followed (management, operations and responsibilities), penalties etc. Each member has equal voting rights regardless of their savings.

Each group possess a metal cash box containing records such as attendance sheets, loans forms, loan records, records on shares purchased, as well as amount collected in each meeting. The cash box is also used to store stamp and stationeries. The cash box (Figure 1) has three locks, one lock in three of the four sides of the box, with the keys being kept by three different members. Though the chairperson is staying with the cash box, he/she cannot open the box. This can only be done during weekly meeting where the three key holders are present. In this case it is impossible for one person to open the box (you need three members to do that). Money collected in each meeting are divided and stored in three bowls (being kept inside the cash box), the first one contain "fines" collected each day, the second one contain the amount collected from the purchase of shares (savings), while the third one

[4] Some groups instead of having collateral groups, they only require a loan applicant to be guaranteed by 2 members.

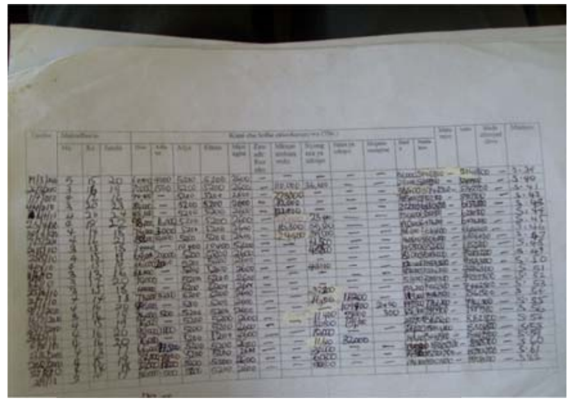
contains members' contribution to the social fund. The amount collected in each meeting is disbursed to loans applicants, with the balance taken is kept in the cash box. In most cases, the amount in the cash box is small as most of the collections during the weekly meeting are is instantly disbursed to loan applicants.

Apart from group records being kept in the cash box, each member maintains an individual "savings book" storing records of all shares he/she has purchased overtime (Figure 3 and 4). The book records the amount of shares a member has been purchasing every week, loans taken and repayment trend. In some groups these savings book are locked in the cash box while in other groups they are kept by members. It is compulsory for each member to bring their savings books during weekly meetings, failing to do so usually attract fines. Each savings book has a unique membership number. When buying shares, the Secretary calls the number of each member and then a member rise and declare publicly the number of shares he/she is purchasing on that day. In some groups very member has to clap hands when a colleague declares any amount of shares she is purchasing. It is a "rewarding" mechanism for abiding to the collective agreement i.e. compulsory savings every week. Only the Secretary is allowed to stamp the number of shares being purchased on the savings book of each member.

These stamps differ from the normal modern ones. They are just specific symbols such as a "cow" or "fish" or "coconut tree". A "cow" symbolizes that one share has been purchased and so on. The reason behind using symbols is to conceal to outsiders that "cows" mean money, in the case the savings book is lost in the streets. Hence, during the purchase of shares the language being used is "one cow", "two cows", "three cows" etc. Each group maintains three types of group funds. The first one is the "empowerment fund" made up of shares being purchased by members and the second one is "social fund" to be borrowed by members for health and education expenditure. Most of these groups have low overhead costs. Management is a voluntary job with major costs being stationeries as well as a payments to the Community Based Trainers (CBT) who visit these groups occasionally. Other costs such as payment for meeting room (for those groups which do not have a free place to meet) have to be shared by each member attending weekly meetings. However, most meetings are held inside a house of one of the member

Figure 1: A cash box with three locks

Figure 2: Management records



Members can purchase between a minimum of 1 share and a maximum of 3 or 5 shares depending on group regulations, with price per share being TShs 1,000 for most groups. The basis for placing the maximum share is to avoid wealthy members dominating the group. As you can see from figure 4, the book has only three columns, meaning that there is a maximum of 3 shares which can be purchased per week. The rows indicate that maximum number of shares have been purchased each week by the owner of that cash book. In some cases when a member faces well known economic shock, members will contribute money to enable her to purchase shares. However, this practice is rare, the same with punishing members for not savings (though they agreed that saving should be done every week by every member). Money collected stays and works within the membership. Once a member is in the group, he/she is complied to retain his/her membership till the end of the cycle as shares cannot be withdrawn prior to that.

These groups maintain "social fund" in which members have compulsory obligation to contribute TShs 1,000 each, every week. Not contributing to social fund attracts a penalty. Social fund is made available to support members on health or education related expenditure; no interest is applied when borrowing from this fund. There is an upper limit a member can borrow from the social fund, as well as maximum frequency which is usually set at three times a year. The principal fund is the "empowerment fund" which is geared towards financing business activities. It is mainly generated from weekly sales of shares. The maximum loan which can be taken from this fund is 3 or 4 times the total individual contributions. For instance if a loan applicant's total savings in the groups is US$ 100, she/he is then eligible to a loan of US$ 300 or US$ 400. However, a loan applicant needs to secure 3 or 4 guarantors within the group, while for some groups the guarantors are colleagues from sub-group. The interest rate is determined by members collectively at the beginning of each round, it is between 5 and 10 percent.

Because members are joint owners, some groups evolve "roundly" after every one year; while it is a year and a half in others. After each round, groups divide the proceeding i.e. dividends and restart a new round. Instead of dividing the profits among themselves, there are cases where groups retain profits as savings for the new round. The profit to be taken by each member of the group at the end of each round depends solely on the number of shares he/she has accumulated overtime. In this case members not only benefit in terms of access to credit but also they earn a return for their investment in these "informal corporate". It is different from the traditional banks, where customers have access to loans but dividends goes to owners of the bank. In the case of these financial self-help groups, members are both owners and customers. Borrowing is not compulsory, and some members can therefore become pure investors i.e. in effect lenders. Due to the need to keep simple accounting procedures, members are not allowed to buy shares they failed to purchase in previously meetings. The main sources of revenue for these groups include interest income from loans, fines collected from members and donations from outsiders. Selling merchandise to members with the profit going to the group fund is another source of group income. In this case, the group purchases a large sack of rice using group fund and divide it into small amount e.g. 5kg for each member to purchase. This means that instead of members buying from the surrounding shops, they buy from within the group at the same market price, with the profit going to the group.

Figure 3: Sample savings book (the cover page)

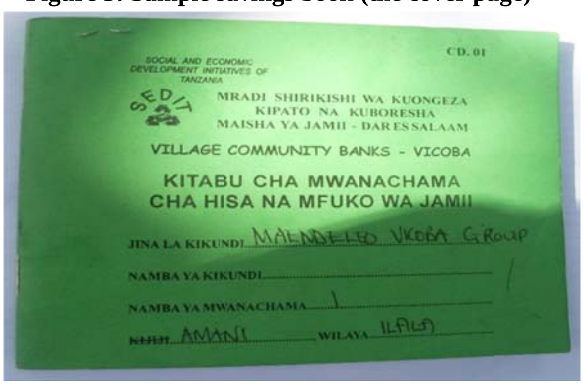
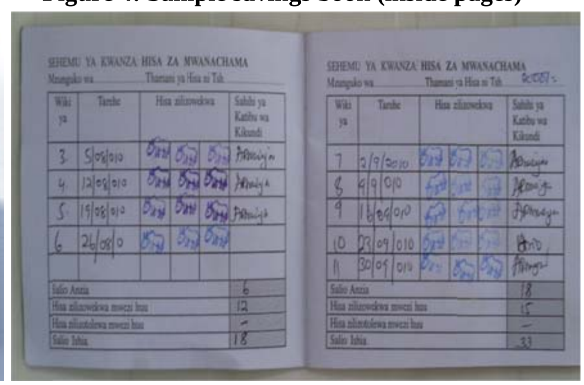


Figure 4: Sample savings book (inside pages)



In some groups, not more than 2 members of the same sub-group can borrow at the same time. The intention of this rule is for most members to have access to loans, especially in situations where loan applications surpass the available funds. This rule is not applicable in the case members from other groups do not apply for loans. When there are less funds than the amount requested for loans, applicants are required to decide how much less each can borrow based on the amount available at that time. Loans are mostly monitored on weekly bases[5]. There are some groups which have stipulated rules on supporting each others during emergency or family events. For instance, when a member looses one of his/her family members, then each group member will contribute TShs 2,000; the same amount during illness. Members also have to contribute TShs 5,000 each to a member whose children are getting married.

5 Repayments begin a month after a loan has been disbursed, weekly scheduled repayments follow thereafter.

Punishment is one of the frequent activities taking place during the weekly meetings. They typically take place in the form of financial reparation and are administered based on offences stipulated in their constitutions. Offences include being late in weekly meetings, sleeping during the meetings, phone interruptions, late repayment of loans, lack of purchasing shares every week etc. (see Table 1 on the list of indirect punishments – those not related to defaulting, and their respective fines). There are cases of members being excluded for consistently failing to purchase shares as well as denial of credit or getting less than a requested amount. Permanent expulsion is always avoided unless the offence is serious e.g. repeated defaulting without explaining to the group. Failing to repay loans usually starts with investigation, followed by informing your partner (husband or wife) about the default. There are also fees applied when outside people visits the groups[6]. The goal of the punishments is to bring the offender in line and there are evidences on coalitions within groups who jointly engaged in punishment. Similar to the findings by Wiessner (2004), the cost of punishment includes (i) loss of a productive or valuable group member (ii) reduced social ties (iii) escalation of minor disputes into a large one (iv) time and energy costs of undertaking punishment i.e. time spent to discuss types of punishment to administer and energy to follow up a member (v) damaged reputation for being too critical or harsh i.e. those who punished can gain negative reputations, for instance, punishing lightly (lelemama) or too harshly (mnoko). The benefits of punishing include limitation of free-riding behavior, bringing offenders back into the line, the expulsion of undesirable group members, and strengthening of bonds within coalitions of punishers.

Table 1: Penalties for different offences

Offence	Penalties (TShs)	Offence	Penalties (TShs)
Telephone interruption	200	Absenteeism from weekly meetings	1,000
Lateness in weekly meetings	200	Not save/buying shares	1,000
Forgetting the saving book	200		

6 There are few cases where the research team had to pay this fee.

3.0 SAMPLING STRATEGY AND TECHNIQUE

The populations of interest for this study are all financial self-help groups in Tanzania[7]. However, the population that was accessible are all groups based in Ilala district in the commercial city of Tanzania (Dar es Salaam)[8]. The sampling frame was obtained from records of the SEDIT and CARE International. There are estimated 244 financial self-help groups in Ilala listed by these two NGOs. SEDIT has facilitated the formation of 60 financial self help groups while Care International has supported 184 groups in Ilala district as of March 2011. The estimated average members per group are 22, yielding a sampling frame (at the sub-unit level) of 5,368 individuals in Ilala. However, I excluded relatively new groups from the sampling frame and include only those which have been operational for more than 11 weeks[9]. This leaves us with 45 SEDIT groups and 164 groups from CARE International. In total I am left with a sampling frame of 209 groups with an estimated membership of 4,598 individuals. Therefore, the representative sample for the 4,598 individuals is computed as follows: -

Confidence interval	=	5 percent
Confidence level	=	95 percent

By using the Z-score table, the confidence level is converted to a Z-score of 1.96. In terms of the proportions, the expectation was 50 percent of the respondents will respond affirmatively. Hence, the sample size is: -

$$\text{SS} = \frac{Z^2 \times P(1-P)}{I^2} = \frac{(1.96) \times 0.50(1-0.50)}{(0.05)^2} = 348$$

Where

$SS = Sample\ size$
$Z = Z - score$
$P = Proportion$
$I = Confidence\ interval$

7 Theoretical population

8 Accessible population

9 The basis for setting 16 weeks as a cutting point is as follows. Groups are not allowed to provide loans until they have accumulated savings i.e. purchasing shares for 11 consecutive weeks. Therefore, loans are provided from the 12th week and because repayment usually start one month after a member has been issued with a loan, then from the 16th weeks repayment (an indicator of cooperation) on schedule or defaulting happens.

However, a much large sample is needed because of the following reasons (i) this study is a multivariate study i.e. large number of variables to be controlled in the analysis; and, (ii) the sample will be broken down into subgroups i.e. these individuals are members of groups, hence our analysis will also need to take into account group level variations taking place at the groups in which these members belong to.

To maximize the number of respondents given the available budget it was decided to conduct the survey at the site where weekly meetings are held. To get respondents from the group the survey needed to select randomly the groups to be visited in order to interview their members. The representative group sample needed to be 136 groups from a sampling frame of 209 groups[10]. Though the representative sample for individual members is 348, the intention was to increase the sample to around 650. Therefore, for 650 respondents, I needed about 45 groups (the assumption is that there is an average attendance of 14 members during those weekly meetings). Therefore, to get from 136 groups to 45 groups to be visited, I applied stage sampling i.e. selecting samples in stages by taking samples from samples. First I selected 136 groups randomly from the sampling frame of 209 groups and thereafter I randomly selected 45 groups from the 136 selected from the previous stage.

While the sample cannot be considered representative of the original population of interest (i.e. the theoretical population of all financial self-help groups in Tanzania), the major purpose of this study was to determine whether specific factors have effects on cooperation in an accessible population. Any evidence of effects or lack of it in this study can be generalized to peri-urban groups that have similar characteristics and operational methodologies to the one considered in this study.

3.1 Survey instrument

Three main salient features of the target audience were considered during the construction of the survey instrument. First, limited formal education and lower reading levels of the respondents. In such a situation the format as well as the wording needed to be as simple as possible. Secondly, as the survey was conducted during weekly meetings, the instrument was shortened in length, covering only those variables which are of high relevant to the objectives of the study. This was crucial as it would have been difficult for members to tolerate long survey because they are also occupied with other responsibilities[11]. In order to save time and be more precise, the format was also made in such a way that will be easy for self reporting e.g. clear boxes for response options. It also adopted forced-choice items rather than free response items. The intention was to have short administration time as well as covering a wide range of themes. To encourage truthfulness in answering, the research instrument did

[10] Recall, 45 groups from SEDIT and the remaining 164 from CARE International

[11] For instance, at the beginning of one of the survey session (late morning of one of the weekends) one of the respondents explicitly requested us to speed up as she needs to cook for her husband.

not require the name or contact of the respondents. Hence, the research team was forthright to the respondents that their responses will be anonymous.

The questionnaire had 4 pages in total given the criteria listed above. This is consistent with several suggestions such as Sudman and Bradburn (1987) in respect of the need to save administration time. At the end of the survey session, all questionnaire where checked for unclear and incomplete response.

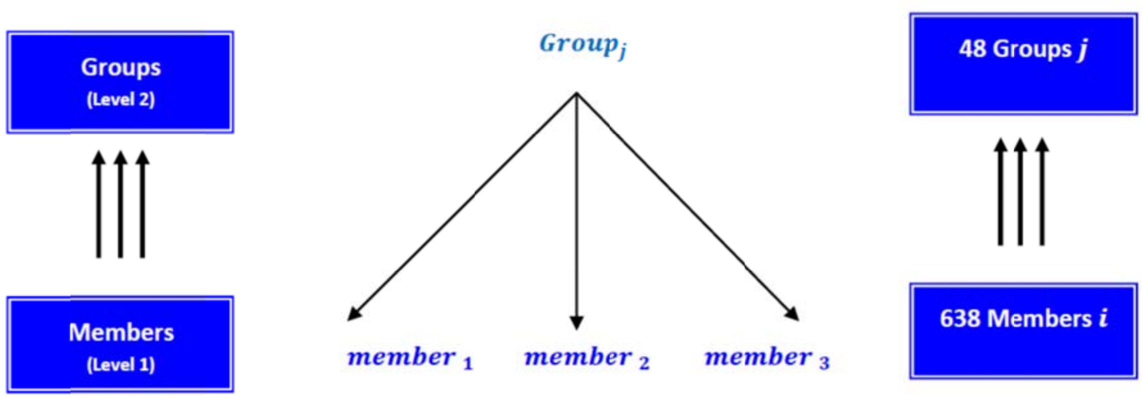
3.2 Data

The data came from a field survey in Ilala district, the capital district, Dar es Salaam. In order to ensure that respondents are able to adequately decipher, recall information and interpret the questions as well as the choices of response listed in the survey instrument, the enumerator was guiding respondents all together question after question. For those who could not read and write (about 12 percent of sample), the enumerators had to undertake face to face interviews. The data structure consists of level-1 (individual members) and level-2 (groups). That is, there are $j = 1, \dots \dots \dots m$ level-2 units and $i = 1, \dots \dots \dots n_j$ level-1 units nested within each level-2 units. Therefore, the total number of level-1 observations across level-2 units is given by

$$n = n_1 + n_2 + \cdots \dots + n_j = \sum_{j=1}^{m} n_j$$

Where $n = 638$ and $m = 48$. The group with the lowest number of respondents had 4 (i.e. minimum n in m is 4), while the one with the maximum number of respondents in the sample had 23 members (i.e. maximum n in m is 23). The average number of respondents per sampled group was 13.3. Hence, the data has two basic levels i.e. the first level is composed of the individual members of the financial self help groups; while the second level refers to the groups. Figure 11 exhibits the two level nested relationships of the surveyed data:

Figure 5: Two-level data structure



The arrows indicate the existing nested relationship in the data. The groups are the individual financial self-help groups, while members refer to the individual members nested within each group. The 48 financial self-help groups in this study are sufficient to apply multilevel analysis[12]. The data structure indicated above, where individuals are nested within groups, means that the estimate of the average repayment rates (the intercept) and/or various repayments sensitivities (the slopes) depend in part on characteristics of the groups in which individuals belong to.

12 According to CMM (2011), to undertake multilevel analysis you need to have at least 20 higher-level units. Centre for Multilevel Modelling, University of Bristol. http://www.bristol.ac.uk/cmm/learning/multilevel-models/data-structures.html generated on 07 November 2011 at 1027hrs.

4.0 RESEARCH PROBLEM

Numerous experimental (Turillo, et al. 2002; Fehr, Fischbacher and Gachter 2002; Fehr and Gachter, 2000), cross sectional (Barboza and Barreto, 2006; Wydick, 1999; La Ferrara, 2003; Ahlin and Townsend, 2007 Wydick, 2001) and ethnographic studies (Wiessner, 2005 and Mahdi, 1986) demonstrate the role of direct punishment on enforcing collective agreements. However, while direct punishment on defaulting has been well documented both theoretically and empirically, the existing literature largely ignores the effects of non-default related punishments on repayment behavior[13]. In other words, most of the discussion in empirical literature is on punishments that are direct related to a particular offence i.e. penalties for defaulting, ignoring the extent to which other penalties influence loan repayment behavior. The question that remains unanswered by the existing literature is: Does non-default related punishments influence repayment decisions? In other words, does indirect punishment produce externalities on repayment behavior?

Furthermore, while it is well documented that peer pressure has positive effects on repayment behavior (see for instance, Wydick, 1999), much less attention has been given to mechanisms influencing peer pressure to have positive effects on loan repayment performance. This has resulted in three weaknesses. First, the literature overlooks the role of indirect punishment as one of the critical element of peer pressure. Secondly, it considers peer pressure as an independent variable mixed up with punishments, and even so focusing on only one type of punishment (the direct punishment related to defaulting)[14]. Third, proxies for punishments are mostly measured as a community level variable rather than as an individual level variable (see for instance, De la Huarte, 2010); in other words, most empirical researches do not have actual data on the frequencies of punishments taking place in economic and social groups. In this research project, the above limitations are address in three ways, first by investigating the spillover effects of indirect punishments on repayment; second, by testing whether indirect punishment is a proximate mechanism under which peer pressure positively affects repayments; third, actual data on frequencies of both types of punishments are used in the statistical analysis. Lastly, given the hierarchical structure of the survey data, one of the key research problems is the examination of the cross-level interactions effects. Specifically, how the group context affects the impact of a dependent variable at the individual members level. This multilevel nature of the data is incorporated in the multilevel statistical modeling.

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13 In their community level index of legal infrastructure Ahlin and Townsend (2007) might have indirectly considered indirect punishments.

14 For instance, the "peer pressure scale" constructed by Paxton *et al* (2000) consist of questions which mixed up both *ex post* and *ex ante* peer pressure i.e. direct punishment was mixed up with other indicators of peer pressure e.g. anger for perceived shirking. This amalgamation ignores one critical factor that direct punishments might be an outcome of "being angry" if we define anger on *ex ante* basis

5.0 LITERATURE REVIEW

5.1 Theoretical background

5.1.1 Punishment concept

Punishment is a human institution, not a natural event outside human purposes, it is therefore deliberately and intentionally organized and practiced (Bedau and Kelly, 2010). Punishment has been defined and debated in many field, from political science, philosophy, psychology to socio-biology as well as in economics. In psychology, punishment refers to an application of adverse stimulus ("positive punishment" or punishment by application) or removal of a pleasant stimulus ("negative punishment" or punishment by removal) aiming at reducing inappropriate behavior (Azoulay, 1999; Carlsmith, Darley and Robinson, 2002; Butterfield, Trevino and Ball, 1996). Examples of positive punishment include criticizing a wrongdoer harshly and openly; while making an offending student loses recess is an example of negative punishment. In psychology punishment is punishment if it leads to a reduction of a bad behavior; otherwise it is not considered punishment. In philosophy, punishment involves the imposition of something unpleasant on a supposed offender for a supposed crime, by a person or body who claims the authority to do so. Philosophers have defined four conditions necessary to define an action as punishment. These include i) punishment is imposed by an authority ii) it involve infliction of pain or something unpleasant to the offender ii) it is a response to an offence, and iv) the person (or animal) upon whom the loss is imposed be deemed at least somewhat responsible for the offence (Bedau and Kelly, 2010).

5.1.2 Punishment in economic groups

Punishment has emerged in economics literature as an additional institution creating incentives to cooperate in collective actions. In microfinance literature, for instance, the introduction of direct punishments and its effects on repayment performance has dominated theoretical work, particularly for group lending mechanisms based on joint liability. In these groups, individual member access to loans depends on the behavior of other members of the group. Several models have emerged focusing on dynamic incentives influencing repayment performance (Besley and Coate, 1995; Armendariz de Aghion, 1999; Banerjee, Besley and Guinnane, 1994; Wydick, 2001). I focus on few models which have captured the salient features of the financial self-help groups under investigation in this study[15].

[15] There are several other theories based on Rotating Savings and Credit Associations (ROSCAs). However, the structure and operational modalities of ROSCAs are fundamentally different from the financial self-help groups I am focusing on, therefore, not relevant for this study

One of the most cited theories on the effects of official and unofficial sanctions on defaulting is Besley and Coate (1995). In this model, group members can potentially employ social sanctions against the defaulter. In particular, the borrower makes the decision whether to pay or not by comparing the repayment amount with the severity of social penalties for defaulting. Within group dynamics, stronger social ties between group members stimulate unofficial penalties resulting in better repayment performance.

In this model, two borrowers exist in a joint liability group, with their decision to repay being made non-cooperatively. The repayment amount is the gross interest rate r (the loan size normalized to one). A borrower invests in an economic project which generates y income i.e. y_i an output of the first borrower and y_j as output of the second borrower. If the lender does not recover full amount from borrowers, which is $2r$, he/she will impose an official penalty, p^0,on each member. The official penalty on borrower i depends on borrower $i's$ output i.e. $p^o(y_i)$. This official penalty is increasing in y, meaning that the higher the income y generated from a borrower's economic project, the higher the official penalty and vice versa. Since penalties depend positively on output, borrowers who realize high returns (low returns) will choose to repay (default).

When weighing repayment r against incurring official penalties $p^o(y_i)$, repayment becomes attractive if $y \geq y(r)$ and default is more attractive if $y < y(r)$. This means that above $y(r)$, official penalties are greater than r and vice versa. To understand whether the group will repay or not, if both borrowers realize income $y_i, y_j < y(r)$, the group will default. This means that official penalties are not strong enough to give incentives for either borrower to pay r. Second, if both borrowers realize return $y(r) \leq y_i, y_j < y(2r)$, the group will repay. This means that both borrowers prefer repaying r to incurring official penalties. Third, if either borrower realize return $y \geq y(2r)$, the group will repay. This is because the more successful borrower will bail out the group if he has to, since paying $2r$ is better than incurring official penalties when returns are high.

The usefulness of unofficial penalties, p^u, emerges in the following scenario, where there is disagreement between the two borrowers with the potential outcome being defaulting. . In this disagreement, neither borrower is willing to bail out the group i.e. $y_i < y(r)$ and $y(r) \leq y_j < y(2r)$. In this case borrower i prefers to default while borrower j prefers to repay, his own share at least, but not for both. This disagreement leads to group default. In this situation, Besley and Coate model introduces unofficial penalties that are imposed on a borrower i say, who decides to default when his partner j would want to repay. Thus, the unofficial penalties depend on two things $p^u(y_i, \Omega_j)$. One is the delinquent borrower $i's$ ability to repay i.e. y_i and secondly, is his partner $j's$ desire to repay, proportion al to his gain from repayment relative to default i.e. $\Omega_j = p^o(y_j) - r$. The effect of the unofficial penalties is to increase the willingness to repay of the low-output borrower in these situations of disagreement. The higher the y_j the stronger are the partner's desire to repay and thus the higher the unofficial penalties p^u. If unofficial penalties are arbitrarily severe, nearly all of these situations result in group repayment, and vice versa if they are arbitrarily weak.

The structure of the Besley and Coate model captures the salient features of the financial self-help groups in this study. The groups are made up of joint liability subgroups in which every member of subgroup is liable if a borrower from that group defaults. The main group, thus becomes the "lender" in the sense of Besley and Coate's model, with the financee being members from sub-groups. As the financer, the group is the one administering official penalty $p^0(y_i)$. Members of the sub-groups are responsible for pressuring and administering "unofficial penalties" to potential defaulters within the same subgroup. Because members have self selected into these groups[16], they are familiar with each other and are roughly aware of the y_i of each member.

The Banerjee, Besley and Guinnane (1994) model place to the forefront the problem of moral hazard i.e. the temptation to gamble with riskier projects, and the ways in which sanctions can address the problem. Because of limited liability for the borrowers, which gives an incentive for borrowers to choose risky project, in this model, peer monitoring (using available local information) is backed by the threat of punishments in case of default. The groups consist of two members, the one who borrows, while the other one monitors (non-borrowing member of the group). The basic assumption is that, projects are selected by the borrower but can be influenced by the non-borrowing member. The borrower receives a loan from the lender and chooses a project with the probability of success p. The project return is $y(p)$ with probability p and zero otherwise. If the project is successful, then the borrower pays r to the lender, if it fails the lender collects q from the monitor (this also means that the monitor is a guarantor). The borrower's payoff is thus $p[y(p) - r] = E(p) - pr$, where $E(p) = py(p)$ is expected output of the borrower. In this case the expected output is increasing in p. It is then assumed that $E'(p) > 0$ and $y'(p) < 0$. The first expression indicates that projects with higher expected returns are also safe. To capture the idea that the borrower will choose projects that are too risky, the assumption is that $p(y(p) - \vartheta)$ where ϑ is the repayment to be made to the lender[17]. Because $y'(p) < 0$ then the borrower would prefer the risky projects.

In this situation the monitor can affect the project choice by setting the penalty c (to the borrower for choosing the risky project) before the borrower chooses his project. The penalty c depends on the probability of project success p and the cost of the loan r that is $c(p, r)$. In this case the cost will depend on the risky p. The minimum penalty needed to enforce project p exactly outweights the borrower's gain from deviating to riskiest project $p = \hat{p}$. It is

16 Van Tassel (1999); Ghatak (1996), and Ghatak (1999) demonstrate how self-selection process of agents into microfinance joint liability groups improves repayment rates through mitigating adverse selection in credit markets. This lead to creation of homogeneous groups with members knowing each other projects.

17 It is lender's opportunity cost of funds.

$c(p,r) = E(\hat{p}) - \hat{p}r - [E(p) - pr]$. The monitor will then choose p to maximize his payoff function which includes the joint liability fee q, paid with probability $(1-p)$ and the monitoring cost of implementing p. The more the monitor monitors, the less likely he will end up paying q. The more monitoring increase the probability of saving on the joint liability fee q. In this situation, the higher rate of joint liability q, increases the advantages of monitoring, hence the higher the payment rates. In short, monitoring coupled with the threat of direct punishment will lead to less risk-taking behavior of the borrower. As for the case of Besley and Coate model, the salient features of the financial self-help groups under consideration are reflected in Banerjee, Besley and Guinnane model.

Several other theoretical contributions have emerged as well in the same spirit of whether punishments influence repayment and under which conditions. De Aghion (1999), for instance, paid particular attention on the design of collective agreements that would induce effective peer monitoring (at a cost) and consequently reducing incidences of strategic default. In her model, borrowers can verify at some cost the true project return of their colleagues and impose social sanctions upon peers who default strategically i.e. those who are unwilling (not unable) to repay. The imposition of social sanctions is considered to be possible based on the same reasons, (as for many other theories) that relative to commercial banks, borrowers in developing countries have a comparative advantage in monitoring each other because of strong social cohesion.

5.2 Empirical literature

The empirical literature on factors affecting cooperative behavior, such as repayment behavior is very diverse. On the particular concept of human cooperation, there have been a growing number of literature addressing the role of rewards and punishments in enforcing collective agreements; while on the particular aspect of repayment behavior, literature has moved away from solely concentrating on personal socio-economic characteristics such as age, gender, income etc., towards institutional factors such as punishments, joint liability etc. Therefore, there is growing number of both experimental and cross-sectional literatures on these subjects.

5.2.1 Experimental and ethnographic studies

An extensive body of experimental and ethnographic literature has focused on investigating the effects of punishments and rewards on the propensity of cooperation among members of social and economic groups. More so, this body of literature has paid particular attention to the question on how human cooperation exists even for genetically unrelated people, and who are not familiar with each other and in some cases they do not even expect to meet after one shot interaction. Because the informal financial self-help groups under consideration are largely depending on the cooperative behavior of individual members, the existing literature on human cooperation highlight both the conditions under which cooperation takes place and the positive and negative incentives in place to enforce compliance to collective agreements. Several laboratory experiments provide evidence that human punish non-cooperators at a cost to themselves as one of the means to sustain cooperation (Fehr, Fischbacher and Gachter 2002; Fehr and Gachter, 2000). For instance, a lab experiment by Fehr and Gächter (2000) consisting of real monetary stakes and two treatment conditions: punishment and no punishment, played in several rounds, find that in the absence of punishment, cooperation decreases, while with punishment, average contributions from players approach 100 percent of their endowment[18]. In fact, the average contribution in the punishment condition was higher in each round than average contribution in any of the rounds of the no-punishment condition with altruistic punishment found to be a common feature in most of the sessions. Details in this study show that 84.3 percent of the subjects punished at least once, with punishment following a clear pattern i.e. most of the 74.2 percent acts of punishment were imposed on defectors (that is, below-average contributors) and were executed by cooperators (that is, above-average contributors). The conclusion from this experiment is that, altruistic punishment[19] of defectors is a reason behind human cooperation, such that cooperation flourishes if altruistic punishment is possible, and breaks down if it is ruled out. What lies behind altruistic punishment is the negative emotion people have towards defectors[20]. As Sigmund (2007) say, by inflicting punishment, members of a society or a group can conceivably turn a defector into a cooperator.

In addition to the altruistic punishment, a concept of strong reciprocity has been tested experimentally and ethnographically to further explain human cooperation and the incentives such as punishments on wrong-doers. Fehr, Fischbacher and Gachter (2002) demonstrate that there exist many people who exhibit strong reciprocity and whose existence greatly improves the prospects for cooperation. It is considered to be a powerful norm enforcement device and may help in explaining the enforcement of food-sharing norms and norms that prescribe participation in collective actions (Fehr, Fischbacher and Gachter, 2002). Similar to the findings on altruistic punishments by Fehr and Gächter (2000), cooperation in the experiment by Fehr, Fischbacher and Gachter is shown to break down in no-punishment condition. At the initial rounds, cooperation is relatively high but over time it unravels and in the final period the absolute majority of the subjects contribute nothing. However, in the presence of punishments if strong reciprocators are given the opportunity to directly target their punishments towards individual defectors, contributions are found to be increasing over time,

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18 Even in one-shot game, the average contribution in a game with punishment is found to be higher than a game without punishments.

19 Altruistic punishment is defined as a punishment undertaken by individual although it is costly for them and yields no material gain (Fehr and Gachter, 2000)

20 The main question in which Fehr and Gächter aim to answer through this experiment was the reasons behind frequent cooperation among genetically unrelated people, in non-repeated interactions; a situation not explain by theories on kin selection, direct and indirect reciprocity, and costly signaling.

in some cases full cooperation is almost achieved. To sum up, Fehr, Fischbacher and Gachter (2002) concluded that the huge difference in cooperation rates across punishment and no-punishment conditions suggests that in the presence of punishment opportunities the strong reciprocators can force selfish individuals to cooperate while in the absence of such opportunities the selfish types induce the strong reciprocators to defect, too. These views are supported in Gintis, et al. (2003) who solicit results from other experiments that have used variety of game structures, confirming the presence of strong reciprocity behavior in human cooperation. And to counter criticisms that experimental games have no counterpart in current everyday life, Gintis, et al. (2003) demonstrate evidence on the consistency between the results from experiments and the degree of cooperation and punishment taking place in everyday life of different societies around the globe.

In addition to the existing experimental evidence, ethnographic data have also confirmed the prevalence and persistence of coordinated punishment as one of the means in which cooperation is sustained in different societies. In these literatures, punishment is coordinated by means of gossip and other communication among punishers such as angry/outright criticisms and complaints, and is not undertaken unless it is legitimate and approved by majority of group members (Wiessner, 2005 and Mahdi, 1986). For instance Mahdi (1986) finds that when undertaking punishment, the punisher is considered to be acting as an agent of the community. In terms of the outcome of punishments, Wiessner (2005) shows that even with verbal criticisms, as one form of punishment, could lead not only to actual changes in behavior but also rallying of group opinion against the offender. He shows evidence of willingness to incur costs in punishment that provided no direct present or future rewards for the reciprocator, which lends some support to the hypothesis of strong reciprocity.

Emerging conclusion from the literature is that if those who free ride on cooperation of others are punished, cooperation may flourish and facilitate the achievements of economic and social objectives in collective agreements. This body of literature confirms the importance of negative incentives such as punishment in enforcing cooperative behaviors (such as repayment of loans, regular savings etc.) in groups such as the informal financial self-help groups, which do not depend of formal enforcement mechanisms such as state organs.

5.2.2 Cross sectional studies

A bulky of literature on repayment behavior has applied different means in testing whether punishment addresses repayment problems. Different terminologies have been used in the literature such as social sanctions, direct (formal) and indirect (informal) penalties, punishments as well as embedding punishments within peer monitoring or peer pressure processes. Nevertheless, microfinance programs and credit cooperatives operating in different parts of the world continue to provide avenues for cross sectional studies that have tested several hypotheses, among others, whether non-contractual incentives mechanisms have positive or negative effects on repayment behavior. While few studies such as Barboza and

Barreto (2006) and Wydick (1999) dispute the positive influence of sanctions on repayment, majority of the literature points otherwise i.e. Increasing probability of loan repayment in the presence of perceived threat of punishments (La Ferrara, 2003; Ahlin and Townsend, 2007 and Wydick,, 2001). For instance Bhatt and Tang (2002) show that direct punishments is not only significant in addressing repayment problems, but its magnitude was higher than other variables used in the model including transaction costs associated with access to loans. Karlan (2011) on the other hand, employs an indirect measure of punishment by examining whether relationships deteriorated after default as a proxy for punishment. While his findings are consistent with others, i.e. peer monitoring and enforcement effectively reduce default rates, he demonstrate that individuals in microfinance programs can filter who to punish because of their strategic defaulting (moral hazard behavior) and who not to punish because of experiencing negative personal shock. Both studies (Bhatt and Tang; and Karlan) have shown that irrespective of the way sanction in encompasses in the model i.e. whether measured directly or assumed to be part of the peer monitoring, it yields the same positive effects on repayments.

Other studies have disputed the influence of punishments on repayment performance. Barboza and Barreto (2006) find that learning by association i.e. peer mentoring rather than peer monitoring[21] is a core element positively affecting repayment rates. The effects of peer mentoring are identified as learning spillovers first from within groups and second across groups. These results show the importance of endogenous learning rather than sanctioning, as one of the means to ensure high repayment rates. On the other hand, using different definition of sanctioning, Wydick (1999) find that peer monitoring significantly effects borrowing group performance through stimulating intra-group insurance; while group pressure is found to have a small effect in deterring moral hazard. As you can see, the two studies Barboza and Barreto (2006) and Wydick (1999) confine different meanings of what peer monitoring is composed of. In the case of Wydick, peer monitoring does not include sanctioning, it is a component of group pressure. This is contrary to Barboza and Barreto where sanction is an integral part of peer monitoring. However, they still arrive to the same conclusion disapproving sanction as a force in addressing repayment problems. While majority of literature has applied only one aspect of cooperation i.e. repayment behavior, Antony (2005) add the production of collective good (loans) as an additional dependent variable and investigate the differential effects both sanctions and reciprocity might have on the two. Sanctions and reciprocity are all found to be positively associated with increased borrowing in microcredit groups i.e. they have influence the production of collective goods. However, contrary to majority of studies on repayment behavior, sanction is found to be insignificant in addressing repayment problems, while reciprocity is important. One important lesson drawn from this study is that the two cooperative processes i.e. productions of collective goods (production of loans) and compliance (loan repayment) are different.

21 Their definition of peer monitoring embedded sanctioning as a core component within. They adopted the definition of peer monitoring from Stiglitz (1990) i.e. peer monitoring means that group members will enforce sanctions against nonpaying members thereby assist in loan recovery.

Rather than considering punishment in isolation, empirical literature has also shown that its influence cannot be separated from other values. De la Huerta (2010) confirms that both cooperation and sanctions are common in environments in which social cohesion is strong. His results, which are consistent with others, suggest that higher repayment rates may prosper in areas in which social ties are strong enough to permit individuals to costlessly enforce agreements in their community, and in which the threat of social sanctions exists and is credible. This means that explaining sanctions without incorporating the role of social ties will deprive an empirical model of the mechanisms in which sanctions are considered to be effective. Though De la Huerta's results confirm the role of penalties on repayment performance, his proxies for both official and unofficial penalties might consists various other items that are not directly related to penalties. In fact while the proxy for unofficial sanctions is similar to direct punishment variable in this study, the one for official penalties might include various other items that are not directly related to penalties. His measure of penalties is at the community level while punishment variable in this article is at the individual level.

De la Huerta's results are consistent with Ahlin and Townsend (2007). When comparing the performance of four different theoretical models[22] Ahlin and Townsend (2007) confirm that the strength of local social penalties as measured by the likelihood of a community-wide lending shutdown to a defaulter, are positively associated with repayment performance. In their study, punishments as an independent variable is composed of community-level variables i.e. availability and quality of institutions (official penalties); and informal sanctions (unofficial penalties). Though unofficial penalty is a community level variable it is similar to the direct punishments variable for the case of this study, as they are directly related to an offence of defaulting. On the other side, the official penalties variable to a certain extent is similar to our indirect punishment approach used in this study. This is because the official penalties approach by Ahlin and Townsend refers to the quality of legal infrastructure which affects both offences related to defaulting and other non-defaulting behaviors.

The literature above and many others do not venture on the effects of indirect punishments on repayment behavior. If we consider repayment as a "behavior" as well as one of the indicator of "cooperation" in the sense of complying to the collective agreements, then it should also be expected that indirect punishments (as defined in this study) might change the behavior of the wrong-doer in other aspects not directly related to the offence to which he/she is being punished. To the best of my knowledge, only Oke, Adeyemo and Agbonlahor (2007[23]) examine the effects of indirect punishment on loan repayment performance. They find that that one unit increment in penalty charges for lateness reduced repayment problems by 0.88 per cent. However, one of limitation of their study is that, indirect punishment is not considered as a core variable in the analytical framework, it is mainly included as a control.

22 These models include Stiglitz (1990), Banerjee *et al.* (1994), Besley and Coate (1995), and Ghatak (1999).

23 The proxy for indirect repayment was penalty for lateness to group meetings.

6.0 ANALYTICAL FRAMEWORK

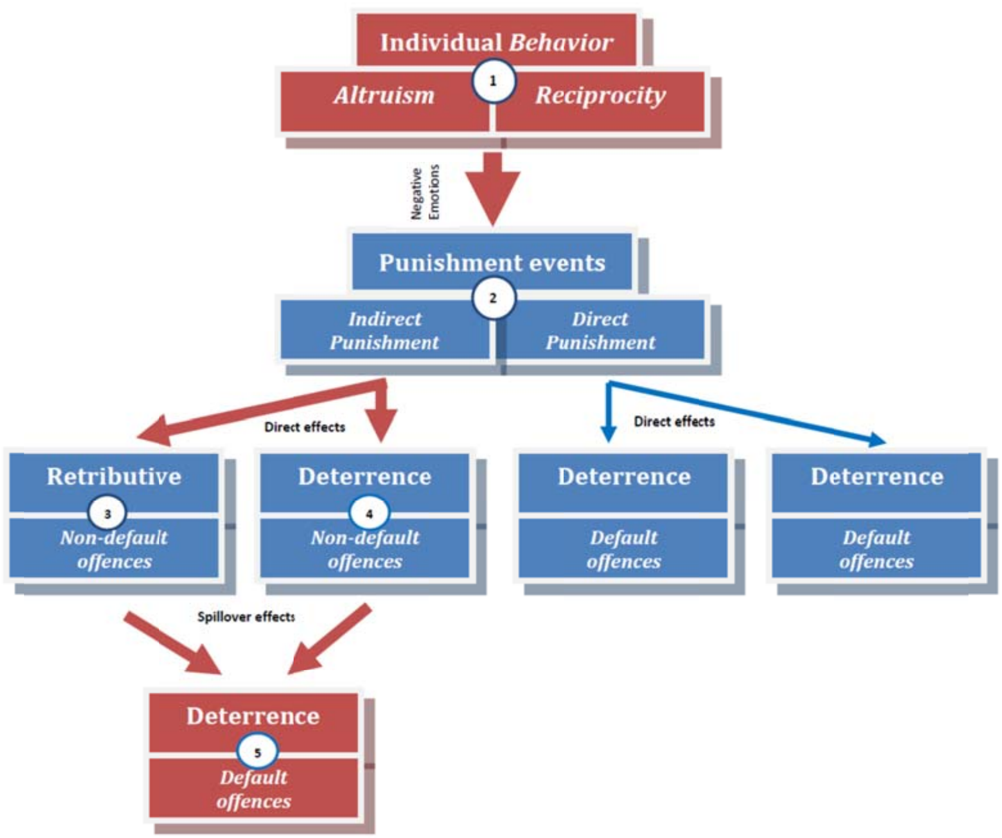
Financial self-help groups are made up of individuals who have shared objectives i.e. joint savings and joint production of a collective good (loans). However, individuals in most of the collective agreements are characterized by conflicts between collective interests and rational private interests i.e. an individual in a collective group will receive a higher payoff for defecting than for cooperating, but all are better off if all cooperate than if all defect (Dawes, 1980; Kollock, 1998; Messick and Brewer, 1983; Dawes and Messick, 2000). Faced with these situations, the success or failure of collective actions will depend not only on common interest and common expected benefits but also on the incentives (rewards and punishments) that would enforce group-beneficial norms such as loan repayment. Therefore, the general theoretical idea is that reward and punishment are behaviors that play an important role in upholding social norms (Boyd and Richerson 1992; Boyd and Henrich 2001; Sober and Wilson 1998; Ostrom, 1990). Within this theoretical proposition, the specific hypothesis in this study is that loan repayment norm, as one of the social norm is affected by indirect punishments, a mechanism through which peer pressure addresses repayment problems.

Figure 12 demonstrates the analytical framework for the territories to be covered. The center box represents the study's key focus-punishment events on non-default related offences, followed by their spillover effects on loan default offences. The first stage in the analytical framework (Box 1), reflects the theoretical proposition in the sociobiology literature, where two groups of theories have emerged in explaining the basis for human cooperation. The first one is based on altruistic punishment (Boyd et al., 2003; Boyd and Richerson, 1992); while the second group encompasses reciprocally altruistic (Fehr & Fischbacher, 2003; Fehr, Fischbacher and Gächter, 2002; Axelrod and Hamilton, 1981; Trivers, 1971). Altruistic behavior refers to the tendency to punish others for norm violation, without expecting any long term personal benefits; while reciprocal altruistic in contrast punish because he/she expects long-term net benefits. The mechanisms behind altruistic or reciprocity behavior is the negative emotion towards norm violators. In other words emotionally driven disposition to return good with good, and bad with bad (Sigmund, 2007).

The presence of both altruist and reciprocity behavior within the informal financial self-help groups leads to the practice of punishment aiming at upholding cooperation. Therefore, the second stage in the analytical framework (Box 2) categorizes punishments into indirect and direct punishments. Following the philosophical literature on the justifications of punishment (see for instance Simmons, A. J., et al, 1995; (Carlsmith, Darley and Robinson, 2002), I conceptualize the indirect punishment to be retributive i.e. it gives wrongdoers what they deserve and restores the kind of moral balance or harmony that the crime upset; and also deterrence i.e. punishment deters future wrongdoings; it is therefore justifiable by its future good consequences (Simmons, A. J., et al, 1995; Lessnoff, 1971) and minimizes the likelihood of future transgressions (Carlsmith, Darley and Robinson, 2002). Hence, indirect punishments which are applied only to non-default related offences, are retributive to the wrongdoers (of those specific non-default offences) and has the deterrence effects as well. In this case, the practice of punishment rests on plurality of values, not on some one value to the exclusion of others (Bedau and Kelly, 2010). That is to say, the main philosophical justifications for punishments i.e. retribution and deterrence, cannot be separated.

The analytical framework therefore indicates that retribution and deterrence purposes of non-default offences has deterrence implications not only on the same non-default related offences but also on potential default related offences, the core aspect of this study. In other words, the offender will be cautioned not to commit offences such as defaulting. Punishment can therefore sustain more cooperation i.e. it can enhance loan repayment norm and this in turn increase the probability of groups to be sustainable. Therefore, group survival which depends on members adhering to group-beneficial norms such as loan repayment requires high levels of altruistic and reciprocal interactions between members allowing for both compliance and production of collective goods to be sustainable.

Figure 6: A framework for understanding the effects of indirect punishments on repayment behavior



Given this analytical framework, empirical exercise is then approached in the following way; if p is the individual probability of loan repayment on schedule and X is the key determinant of p, the key approach is then to determine $\partial p/\partial X$ where the X is made up of two groups of variables i.e. punishments, and the controls.

7.0 EMPIRICAL MODEL

As elaborated in the literature review, punishment may affect repayment behavior in collective agreements. In this empirical analysis I investigate whether punishment on offences not related to loan defaults play a role in repayment behavior in the context of financial self-help groups in Tanzania. My dataset include information on two types of punishments i) punishment for defaulting; and, ii) punishment on other offences not related to the repayment of loans.

Because of the binary nature of the dependent variable, this study opted for a logit statistical model to estimate the effects of punishments on repayment behavior. It is a model that will ensure the predicted values lies within the interval [0,1]. Another key feature of the data, as elaborated in Section 4, is the way in which respondents are clustered at the group level, necessitating a multilevel modeling[24]. Technical advances have been made on multilevel models over the past several years (See for instance Bryk and Raudenbush, 1992, Goldstein, 1995; Kreft and DeLeeuw, 1998; Leckie, 2010; and Steel, 2008, 2009). The multilevel models recognize the existence of clustered data by allowing for residual components at each level in the clusters i.e. variations at the group level (i.e. level-2), and variation attributable at the individual member level (level-1). In addition, the effects of both unobservable and observable variables (unobservable and observable group characteristics) can be separately estimated. Traditional multiple regression techniques treat the units of analysis as independent observations; leading to the underestimation[25] of standard errors if the data are hierarchical in nature[26].

Formally, consider the existence of a two-level structure where a total of n individuals (at level-1) are nested within j groups (at level-2) that is with n_j individuals in group j. The study observes y_{ij} as the binary response for member i in group j (with a respondent responding either $y = 0$ or $y = 1$). The probability of the response being one is given as

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24 Sociologists have been at the forefront in the use of multilevel models for binary data, adopting logistic or probit regression techniques as their standard analytical tools. Guo and Zhao (2000) outline two reasons behind this. First, sociologists, perhaps more than any other social scientists, are interested in explaining and predicting phenomena that can be characterized by a binary variable e.g. marrying, not marrying, divorcing or not divorcing, in school or not in school, voting for party A or party B. The second reason that prompted an interest in multilevel models is the practice of examining hierarchical social structure. Because social structures are often hierarchical, multilevel models have a natural appeal to sociologists. For instance, in schools, students(level 1) are nested in classes (level 2), and classes are nested in schools (level 3); individuals are nested in families, and families are nested in communities or neighborhoods etc. (Guo and Zhao, 2000).

25 Hence, overestimation of the statistical significance.

26 Guo and Zhao (2000), Steel (2008) explain challenges associated with the applying single-level multiple regression model for multilevel data. These are related to the inclusion of a set of dummy variables for groups as explanatory variables (fixed effects model) in the model especially when the number of group is large.

$\pi_{ij} = Pr(y_{ij} = 1)$ with y_{ij} following a Bernoulli distribution. The probability of responding one, π_{ij} is transformed using the logit link function[27] $Pr(y_{ij} = 1) = \pi_{ij} = e \ \ /1 + e$ which links π to the explanatory variables i.e. mapping a probability π lying between 0 and 1, to any value in the range $(-\infty, +\infty)$. Then, the model to be considered is:

$$logit(\pi_{ij}) = log\left(\frac{\pi_{ij}}{1-\pi_{ij}}\right) = \beta_0 + \beta_1 x_{1ij} + \cdots + \beta_p x_{pij} + \mu_j = \beta_0 + \sum_{p=1}^{P} \beta_p x_{pij} + \mu_j \qquad (1)$$

Where $\mu_j \sim N(0, \sigma_\mu^2)$

i	=	$i, \ldots \ldots \ldots\ n_j$ individuals within the groups.
j	=	$j, \ldots \ldots \ldots\ N$ groups (financial self-help groups)
p	=	subscript for independent variables. There are P number of x_s where $x = x_1, x_2, \ldots \ldots \ldots . x_p \in R^p$ is a vector of p independent variables.
x_{pij}	=	the value of the variable p for an individual i who is nested in group j. The i and j subscripts on x show that its values vary from individual to individual within a group.
β_0	=	is the overall intercept i.e. the overall mean of y (across all groups)
μ_j	=	is the difference between group $j's$ mean and the overall mean. It is a random effects at level-2

Model (1) is considered as a combined model (i.e. combining both level-1 and level-2 models). Disaggregating it we get, level-1 model as:

$$logit(\pi_{ij}) = log\left(\frac{\pi_{ij}}{1-\pi_{ij}}\right) = \beta_{0j} + \beta_1 x_{1ij} + \cdots \ldots \ldots + \beta_p x_{pij} = \beta_0 + \sum_{p=1}^{P} \beta_p x_{pij} \qquad (2)$$

Without μ_j, the level-1 model is the standard logistic regression model. Because of the fact that intercepts are random i.e. each group has different intercept, this means that the intercept β_{0j} is broken down into two parts. An overall or average value of the intercept i.e. β_0 and a group dependant part of the intercept μ_j giving a level-2 model as:

$$\beta_{0j} = \beta_0 + \mu_j \qquad (3)$$

[27] The link function is the function of the probabilities that results in a linear model in the parameters. It is based on the logistic transformation of $\beta_0 + \sum_{i=1}^{P} x_i$ and is the cumulative distribution function of a logistic distribution.

Model (3) means that the intercepts of each group line will have the same β_0, making the differences between the groups' intercepts to depend on the value of μ_j which is the difference between the overall mean value of the dependent variable and the mean value of the dependent variable in group j[28].

Given the objectives of the study, where factors associated with repayment behaviors are assessed, in the logistic regression model above, π_{ij} is a conditional probability of the form $P\left(y = 1|x_1, \ldots, x_p\right)$. That is, it is assumed that $y = 1$ is more or less likely depending on combinations of values of the predictor variables. The importance of this transformation is that, $logit(x)$ has many of the desirable properties of a liner regression model. The logit of the probability of an event given x is a simple linear function i.e. the log-odds changes linearly as a function of explanatory variables, it is linear in the explanatory variables, may be continuous, and may range from $-\infty\ to + \infty$, depending on the range of x.

The common approach to multilevel modeling is to fit a series of models, testing at each step the plausibility of the different hypothesis raised in this study. In our case, three models will be tested. Model I includes individual-level effects only, to compare against models including different forms of group-level variation (Models II-IV).

Model I: Single level logistic regression

Level-1 model depicted by (2) is the single level logistic regression. The model contains only the fixed part of the multilevel logistic regression i.e. The parameters that are to be estimated are β_0, β_1 ... . This model ignores the existence of hierarch of the survey data and therefore the unobservable variations at the group level are not considered. The only unexplainable variability in this single level logistic regression is the variance of the error term. Each observation is treated an independent information in the computation of the standard errors of the coefficients.

Model II: The variance component model

This involves fitting the data to the unconditional means model, a simple model that omits explanatory variables. Its primary objective is to investigate the extent of the heterogeneity between the clusters (i.e. groups), thereby establishing the rationale for analyzing an extended

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28 The importance of logit function (1) and (2) is that the function can take as an input any value from negative infinity to positive infinity, whereas the output is confined to values between 0 and 1 (the output is referred to the LHS representing the probability of a particular outcome, given that set of explanatory variables; while the input is the RHS i.e. the exposure to some set of independent variables). For statistical theoretical reasons, logistic regression analysis is based on a linear model for the natural logarithm of the odds. Taking the natural logarithms of the odds, changes the scale from 0 to ∞ (for odds), to $-\infty$ to $+\infty$ for log odds, centered on 0 (For technical guidance on the critical application of natural logarithms to the odds, see for instance Tarling, 2008; Azen and Walker, 2010).

multilevel model that would include independent variables (Glaser and Hastings, 2011). In the model, the *overall intercept* β_0 is shared by all groups while the *random (group) effect* μ_{0j} is specific to group j. The random effect is assumed to follow a normal distribution with zero mean and constant variance $\sigma^2_{\mu_{oj}}$.

$$logit(\pi_{ij}) = log\left(\frac{\pi_{ij}}{1-\pi_{ij}}\right) = \beta_0 + \mu_{0j} \quad (3)$$

This model without any explanatory variables will produce an equation with an intercept but without a slope. The unconditional model gives the log odds of the dependent variable for the level-1 units (individual group members) across the level-2 units (the groups). It also partitions the variance between level-1 and level-2; with the between-group variance then representing the differences between the groups at level-2. The parameters to be estimated are is the β_0 and σ^2_μ (and not the μ_{0j}).

Model III: The random intercept model

Model (1) is called the random intercept model. It is testing the proposition that the intercept, i.e., the average repayment rates given the average values of the independent variables varies between groups. The model consists of two parts, the fixed and random part. In this model the intercepts of the group regression lines are allowed to vary randomly across groups i.e. the intercepts are allowed to take on different values from a distribution (Steel, 2008). However, the slope for each regression line remains the same i.e. parallel group regression lines. The inclusion of multiple independent variables allows for the study to focus on the variables of interest while controlling those which are considered to have some effects on the dependent variable. In other words, for instance β_1 is the effect of x_1 for individuals with the same value of x_2 and so on.

The above multilevel random intercept model consists of two parts (i) a fixed part – specifying the relationship between the dependent and independent variables (ii) a random part consisting of level-1 and level-2 residuals. The fixed part is

$$\beta_0 + \sum_{p=1}^{P} \beta_p x_{pij}$$

With the random part being μ_j. The intercept does depend on level-2 units (i.e. groups in our case). However, the regression coefficients (slopes) of the independent variables $x_1, \dots x_p$ are constant. This means that the model permit the estimation of the unexplained variability in the intercepts β_{0j} across level-2 estimates.

8.0 EMPIRICAL RESULTS

8.1 Variable descriptions

8.1.1 Dependent variable

The dependant variable in the analysis is REPAY, a binary variable that may be 0 or 1. In particular, REPAY = 1 if a group member indicates that she/he has either defaulted or done late repayment of his/her loans; while REPAY = 0 if a group member indicates that he/she has repaid on schedule. Repayment usually begins one month after obtaining the loan, and should be completed within 12 weeks (three months). Failure to start repayment in the first 4 weeks and after the 12 weeks warrant punishment from the group i.e. *punishment directly related to an offence of late repayment*. It is in the discretionary power of the group to decide the kind of punishment depending on the balance remaining. Hence, my question on late repayment refers to both failure to repay the first installment (after 4 weeks) and after the 12 weeks. In the empirical analysis, we have only included members whom have taken loans from these groups i.e. excluding members who are yet to apply for loans.

8.1.2 Independent variables

Our dataset include information on the two categories of punishments i.e. punishment for defaulting and punishment associated with other offences not related to credit defaulting. In particular, we have used the following individual level independent variables to measure these two types of punishment within the groups: -

Table 2: Punishment variables

Variables	Descriptions
Indirect punishments	=0 If a group member has been punished (within the group) in the past 12 months by his/her colleagues on offences not related to credit repayment; 1 otherwise. Penalties are listed under Table 1. The expected direction of influence +ve.
Direct punishments	The proxy used for the punishments given to defaulters is the presence or absence of perceived threat of punishments in the event of loan default. If a group member considers that the threat of punishment for late repayment is credible (=0); while it is 1 otherwise. The hypothesis is that the higher the percentage of members who believe that punishment for default is credible, the higher the likelihood punishments for default taking place. The direction of influence on repayment behavior is expected to be +ve. The same variable has been used by Bhatt and Shui-Yan (2002).

Next to these variables measuring punishments, I also use a number of variables measuring personal characteristics of group members. These set of variables are used as control variables. The reason why we include these variables in our analysis is that personal characteristics might influence repayment behavior in groups. They are not of major interest, but it is important to adjust for their effects to obtain more meaningful estimates of punishment effects, that we are interested in.

Table 3: Personal characteristics and socio-economic variables

Variables	Descriptions
Age	Age was measured in years at the time of the survey. However, in the statistical analysis it is categorized as equal to 1 if the respondent is between 30 and 39 years old; while 0 otherwise; This means that the dummy = 0 if the respondent is young i.e. 29 years of age and below as well as old age 40 years and above (similar categorization as Papias and Ganesan, 2009). Diverse results exist in the literature. One of the reasons for diversity is that, researches focusing on different economic sectors would yield different results on the effects of age. Empirically, young people repay their loans on schedule than old people (Eze and Ibekwe, 2007; Godquin, 2004).
Education	It is equal to 0 if the respondent has attended formal education; 1 otherwise. By formal education I refer to the traditional definition of primary school and above. Empirically, negative effects on repayment trends (Matin, 1997) while positive impacts on one's likelihood of repaying (Bhatt and Tang, 2002; De la Huerta, 2010[1]; and Papias and Ganesan, 2009).
Income	I resorted to monthly expenditure estimates as a proxy for income. Individual estimates are categorized as equal to 0 if expenditure is less than the grand mean expenditure and 1 if expenditure is above the mean income. The hypothesis is that the higher the income, the higher the probability of repaying on schedule. In some empirical literature, income has been found to have positive influence on repayment behavior (Oke, Adeyemo and Agbonlahor, 2007); while it is negatively correlated with repayment performance (Hermes, *et al* 2005) and statistically insignificant (Bhatt and Tang, 2002).

Although the main interest is on how punishment affects repayment behavior, there are also important non-punishment influences to consider. We specify social ties, savings, outside options and homogeneity of preferences as another set of control variables. We define them as follows:

Table 4: Other control variables

Variables	Descriptions
Homogeneity of preferences	In essence, all groups consider the principal objective of these establishments is access to finance. Hence, services provided by groups are categorized into two segments i.e. the first segment refers to the core services i.e. loans and savings, while the second group is non-core services , for instance, consoling each other when a member experience social shock etc.[29]. The responses are coded, = 0 if the respondent has attached a high value to the core services i.e. they prefer loans and services than non-core services. Social identity theories demonstrate that groups in which members are linked by a collective identity will cooperate (Taylor and Whittier 1992; Hercus 1999; Cerulo 1997). Empirically it is shown that homogeneity of preferences may help groups in achieving high repayment rates (Bhatt and Tang, 2002; Anthony, 2005). While attaching high value to having access to loans reduces the probability of moral hazard behavior, especially so for group leaders than for other group members (Hermes, Lensink and Mehrteab, 2004)
Social ties	Number of friends in the group is taken as a measure of social ties. The hypothesis is that the higher the number of friends in the group, the higher the likelihood a member has strong social ties in the group. = 1 if a respondent is having 0 friends in the same group, = 2 between 1 and 2; and lastly = 3 if having more than 2 friends in the group. The variable is exogenous because the survey question refers to friends before the formation of the group rather than friends after the group formation. It is expected that information flows will be higher for people with many friends in the same group leading to low probability of defaulting (-ve sign). However, as indicated by Sharma and Zeller (1996) cultural factors may make it difficult to impose sanctions on close friends and in this way dilute the enforcement process (+ve effects). On the theoretical side, literature has postulated +ve implications of social ties on loan repayment (Floro and Yotopolous, 1991; Stiglitz, 1990; Varian, 1990; Rashid and Townsend, 1992; Besley & Coate, 1995). Empirically, social ties seems to cement a positive role on cooperation e.g. loan repayments (Zeller, 1998; Hermes, *et al* 2005; De la Huerta, 2010); negative implications (Paxton *et al*, 2000; Wahid, 1994; Devereux and Fishe, 1993; Ahlin and Townsend, 2007; Sharma and Zeller, 1997) and it is sometimes statistically insignificant (Wydick,1999).
Compulsory savings	Refers to the number of shares purchased weekly (on average). For those buying medium to small number of shares per week = 1 (buying between 1 and 3.5 shares) while for those buying large amount of shares (between 4 and 5) are coded as reference group i.e. = 0. The requirement for members to purchase shares frequently i.e. on weekly basis, enables members to form the habit of saving regularly. At the same time, it serves as a savings mechanism for group members who do not have regular access to banking services. Theoretically, introducing compulsory savings reduces the payoffs of risky projects at a higher rate than in the case of safe projects (Stiglitz, 1990); increasing the probability of selecting safe projects (Banerjee *et al,* 1994); and an increase in official penalties in the case of defaulting (Besley and Coate, 1995). Empirically, savings improve repayment performance via improved financial discipline and acting as collateral (Zeller, 1998; and De la Huerta 2010).
Outside options	This question was whether an individual is a member of other financial institutions i.e. =0 and 1 otherwise. In the theoretical field outside options drives out of the market safe type borrowers (Ghatak, 1999). The relationship between outside options and repayment behavior emerged with contradicting results from the empirical literature. To be a member of outside similar organizations contributes positively to repayment behavior (Oke, Adeyemo and Agbonlahor, 2007; Paxton *et al*, 2000); while it has negative impact (Matin, 1997; Hermes, *et al* 2005; De la Huerta, 2010; Ahlin and Townsend, 2007). One reason behind positive association is that the same set of people who are creditworthy, in e.g. cooperative societies will also be in microfinance groups (Oke, Adeyemo and Agbonlahor, 2007), while having loans from other groups is an indication of creditworthiness rather than having obligations spread too thin (Paxton *et al* (2000). It is however perceived that, switching between groups reduces social ties and consequently lead to repayment problems (Hermes, *et al* 2005).

29 Some similar financial self-help groups outside Dar es Salaam accommodate environmental conservation objectives as well, for instance, prohibiting businesses that are not environmentally friendly (Wild, Millinga and Robinson, 2008)

The expected sign for homogeneity of preference is positive, that is if a group member considers credit to be a high value group service compared to other services offered by the group, this will encourage them to behave prudently, thus reducing the probability of late repayment or defaulting. For SOCIAL TIES, the expected sign of coefficient cannot be predicted because of the two forces as explained above. Compulsory savings is expected to have a positive sign. The higher the number of shares being purchased the higher is the incentive to enforce loan repayments. In addition, I include a variable to measure outside borrowing opportunities. The sign cannot be predicted given different theoretical predictions.

Table 5: List of independent variables, definitions and expected signs

Variable	Symbol	Variable definition	Exp. sign
Punishment Credibility	direct_pun	=0 if punishment for defaults is considered credible; =1 otherwise	+
Other punishments	indirect_pun	=0 if ever punished for other offences (not default); =1 otherwise	+
Monthly income	income	=0 if monthly income < than the grand mean income; =1 otherwise	+
Social ties	social_ties	=0 if 1 friend ; =1 between 1 & 2 friends; =3 if ≥ 3 friends	?
Age	age	=1 if respondent is between 30 and 39 years (inclusive); 0 otherwise	?
Education level	education	= 0 if respondents attended formal education; =1 otherwise	+
Outside options	options	= 0 if a member of other financial institutions; 1 otherwise	-
Preferences	preference	= 0 loans and savings; = 1 other services	+
Savings	savings	= 0 if between 4 & 5 shares; = 1 between 1 and 3.5 shares per week	+

Notes: (+) positively associated with the repayment behavior of the borrowers; (-) negatively associated with the repayment behavior of the borrowers; (?) direction of association with repayment behavior is not known.
Dependent variable: REPAY = 1 if a member has defaulted or done late repayment; = 0 if he/she has repaid on schedule

To avoid arbitrary selection of the *reference category*[30] (=0) when coding the dummy variables, following Hardy (1993), the reference category is a category with ample number of cases for reasons related to sample size and error. Furthermore, the number of dummy variables necessary to represent a single variable is equal to the number of levels (categories) in that variable minus one i.e. if there are p categories, I use $p-1$ dummy regressors. Hence in all cases above because there were two categories, I have created one dummy per the original variable i.e. $p = 2$ hence $2 - 1 = no. of\ dummies = 1$.

8.2 Descriptive statistics

First, for the dependent variable REPAY, about 76 percent have repaid their loans on schedule compared to 24 percent who have repaid late. This is somehow a good repayment rate. However, if we want to consider other performance indicators, e.g. profitability, then further data on repayments will be required. For instance, you will need further information on whether defaulters are small borrowers and the re-payers are large borrowers or the other way round.

30 Against which the other categories are compared.

While repayment behavior can be considered as one of the indicators of cooperation in collective actions, I compared this variable with other potential indicators of cooperation. The other two indicators of cooperation i) meeting attendance ii) savings[31]. By cross-tabulating repayment behavior with the frequencies of meeting attendances and savings, it is shown that 69 percent of those who repaid on schedule are the ones purchasing large amount of shares (i.e. more than 3 shares per week[32]). This is an indication that a majority of those investing more have better credit repayment behavior. The same pattern is observed when repayment behavior is cross-tabulated with meeting attendance. In this case 98 percent of those who have repaid their credit on schedule are frequent participants of the weekly meetings. This is compared to 63 percent who defaulted but are also frequent participants of the weekly meetings. Overall, by comparing repayment behavior with frequency in attending meetings and weekly saving behavior, then majority of those fulfilling collective agreements (attending meetings and save weekly) are repaying their loans on schedule.

Table 6: Statistics for continuous variables

Variable	Obs	Mean	Std. Dev.	Min	Max
Friends	638	4.252	4.371	0	30
Age	638	40.260	10.809	18	78
Education	638	2.019	1.531	1	5
Savings	638	4.092	1.128	1	5
Meeting attendance	638	9.613	2.248	2	12
Expenditure	638	121843.3	92535.4	4000	600000

There are two punishment variables in this study i.e. direct and indirect punishments. Results show that most members (80 percent) believe that the threat for punishment for default is credible, with only 20 percent thinking otherwise[33]. The indirect punishment was a binary variable as well =0 if ever punished for offences not related to credit repayment and 1 otherwise. Indirect punishment appears to be a common phenomenon in these groups with 67 percent had experienced these punishments compared to 33 percent. As members are nested into groups, there is high variation at the group level regarding punishments on other offences not related to credit repayments. That is, about 64 percent of those who have experienced indirect punishments are nested into 22 of the total 48 groups sampled in this study.

[31] On one hand, purchasing weekly shares can be as considered more of an investment decision than an indicator of cooperation. However, on the other hand, it a collective agreement that purchasing shares every week is compulsory. It is therefore more relevant to consider it as an indicator of cooperation rather than an investment decision.

[32] Recall that the maximum amount of shares a member can purchase per week ranges between 3 and 5.

[33] Rather than asking a question on whether a member has been "directly" punished, the survey question was based on the perceptions about the credibility of direct punishments. This is considered as a proxy of the presence of direct punishments.

The role of social capital has emerged as a core element in most literature on collective actions. It is a theoretical justifiable determinant of cooperation, also an important aspect in members selecting themselves into groups (self selection process) i.e. groups are formed by people who have known each other for some time. An indicator of social ties adopted for this analysis is the number of friends a respondent has in the groups. On average members were having 4.4 friends in the same groups and the standard deviation is 4.3. This evidences the need to control social ties in the in the statistical model. As indicated earlier, this variable is exogenous as the number of friends considered where those existing before groups were formed.

Descriptive statistics for personal characteristics such as age and education reveal some variations as well. The average age is 40 years with a large standard deviation of 10.8 years. Furthermore, 35 percent of respondents are found to be between 30 and 39 (inclusive) years of age. This is a young group, while the remaining 65 percent is composed of old generation of above 40 years of age (and very few young people below 30 years). In short, most members are aged, and this can be expected, as membership required people who can save on weekly basis, a characteristic of mostly employed or entrepreneurs rather than dependables. Most group members are primary school educated, they have on average spent 6 years in formal schooling with a large standard deviation of 3.7. In fact, 81 percent of respondents have attended formal education, with the remaining 19 percent are illiterate. Though 19 percent sounds small, it is big when considered in absolute terms. It was surprising that in the capital, urban region where access to public education is relatively easier that in rural areas, such large number of people could not access primary education. With the majority having primary school education, and given the ongoing public debate on the poor quality of primary school education[34], there is low probability that the education variable in this study will justify the theoretical prediction that formal schooling is an indicator of human capital expected to influence efficiency positively and thereafter address repayment problems. On the income side, members spend about TShs 121,843 per month on average, with a high standard deviation of TShs 92,535. This shows large variation on income level between individual members. In particular, about 58 percent of those in the sample are having monthly income less than the grand mean, with the remaining 42 percent being above the grand means. Therefore, majority of members in the sample are poorer compared to the overall grand mean.

Recall that when a group is formed, members accumulate savings for 16 weeks consecutively without having access to loans . However, during this period indirect punishments are administered (while direct punishment as per my definition do not exist -because there are no loans and therefore no defaults to administer direct punishment). The hypothesis that indirect

[34] Recently released independent evaluation of primary education sub-sector revealed shocking results. Among other these include, one in five primary school leavers cannot read Standard 2 level Kiswahili; half the children who complete primary school cannot read in English, and; only 7 in 10 primary school leavers can do Standard 2 level Mathematics (UWEZO, 2010).

punishment as a proximate mechanism of peer pressure can be tested by cross tablating repayment behaviour (i.e. REPAY variable) with the frequencies in which creditors have been punished indirectly (i.e. INDIRECT_PUN variable). The hypothesis is that members who have been ***indirectly*** punished more frequently repay their loans on time compared to those who have been ***indirectly*** punished less frequently. That is by experiencing indirect punishment frequently, they behave well (repay on time) when loan are issued i.e. after the 16 weeks of continous savings. In other words, ***indirect*** punishment has spill over effects on repayment behaviour. Results are demonstrated in Appendix 1. It is shown that, of those who have repaid loans on schedule, 70.95 percent experienced indirect punishments compared to 29.05 who never experienced indirect punishments. Furthermore, of those who never experienced indirect punishments, only 29.05 percent repaid on time, while 45.51 percent defaulted. These results suggest that by experiencing indirect punishments, members expect a stronger reaction from the group if they dare commit an offence of defaulting i.e. strong negative emotions of punishers on wrong-doers will continue even when loans are issued and defaults happen.

8.3 Univariate analysis

The reason behind using univariate analysis is the limitation of the goodness of fit test such as Akaike's Information Criterion (AIC). AIC requires a series of candidate models specified a priori. This means if only poor models are considered, the AIC will identify the best of the poor models; even if all the models are poor (Burnham and Anderson, 2002). This highlights the importance of working from the univariate statistical analysis, after taking into account the system under investigation and theoretical justification of the variables. To identify important covariates – the ones that are at least moderately associated with the dependent variable, I fitted a standard logistic regression model with one covariate at a time and analyze the fits. I opted for this approach rather than stepwise elimination because the potential for residual confounding is substantial – as the model will only include regressors that are statistically significant at $p < 0.05$ (see for instance Vittinghoff et al, 2005). Basically, I am testing the null hypothesis $H_0: \beta_1 = 0$, (i.e. the data is completely random, that there is no relationship between two variables.

The critical z-score values when using a 95 percent confidence level are ±1.96 standard deviations, and the p-value associated with a 95 percent confidence level is 0.05. The z-score for five variables i.e. direct punishment, indirect punishment, social ties and preferences lay outside ±1.96, giving p-values of less than 0.05 (less than 1 in 20 chance of being wrong), hence rejecting the null hypothesis; i.e. the relationships exhibited are unlikely to be one version of a random pattern. Table 7 demonstrates the z- and p-values for each of the tested covariate. The common rule of thumb in the literature is to include all covariates whose p-value < 0.25 (McCracken, 2004)[35]. Table 4 demonstrates that the indirect punishments are highly statistically significant as $p < 0.001$ (less than one in a thousand chance of being wrong). Furthermore, “gender”, “marital status”, “age”, “education” and “income” as insignificant. However, we include “income” in the final model because of its clinical importance when assessing repayment behavior. Age, savings and education are included as well following the standard rule of thumb as their p-values are less than 0.25.

Table 7: Univariate analysis

Parameter	Description	Z-values	p>|z|
Direct punishment	=0 if punishment for defaults is considered credible; 1 otherwise	2.65	0.008
Indirect punishment	=0 if ever punished for other offences (not default); 1 otherwise	3.56	0.000
Income	=0 if monthly income is less than the grand mean income; 1 otherwise	0.06	0.951
Social ties	=0 if 1 friend ; =1 between 1 & 2 friends; =3 if ≥ 3 friends	3.06	0.002
Age	=1 if respondent is between 30 and 39 years (inclusive); 0 otherwise	-1.31	0.189
Gender	=1 if male; = 0 female	0.52	0.604
Education	=0 if respondents attended formal education; 1 otherwise	1.26	0.207
Outside Options	= 0 if a member of other financial institutions; 1 otherwise	1.20	0.232
Preferences	= 0 loans and savings; = 1 other services	3.00	0.003
Savings	= 0 if between 4 & 5 shares; = 1 between 1 and 3.5 shares per week	1.62	0.106
Marital status	=1 if married; 0 not married and widows	0.83	0.409

8.4 Diagnostics

8.4.1 Specification error

Our model has assumed the logit of the dependent variable is a linear combination of the independent variables. Other additional assumptions, include, first, the logit function (in logistic regression) is the correct choice as our link function to use. Secondly, on the right hand side of the regression equation, I have included all relevant independent variables. In this section specification error is tested to confirm whether the model has all relevant independent variables and if the dependent variable is a linear function of the predictors.

If the model is properly specified, we should not be able to find any additional predictors that are statistically significant except by chance. Two values are used as independent variables to rebuild the model, first is the linear predicted value (_hat) and secondly, the linear predicted value squared (_hatsq) as the predictors to rebuild the model. The variable _hat should be a statistically significant independent variable, since it is the predicted value from the model. On the other hand, if our model is properly specified, variable _hatsq shouldn't have much predictive power except by chance [UCLA ATS, 2012).

[35] Several other literature such as Maldonado and Greenland (1993), Budtz-Jørgensen et al (2006), Gusti (2009) suggest that potential variables be eliminated only if p > 0.20, in order to protect against residual confounding.

Table 8: Results of the model testing specification error

Parameter	Estimate	Z-values	p>|z|	Standard errors
_hat	0.763	2.09	0.036	0.365
_hatsq	-0.125	-0.71	0.481	0.177
β_0 (Constant)	-0.060	-0.30	0.764	0.201

The first approach was to run the normal non-multilevel logit regression[36]. Table 6 shows that, the variable _hatsq is not statistically significant (with p-value = 0.481) while _hat is statistically significant. This gives two confirmations; first, that meaningful independent variables have been selected in the model. Secondly, since the _hatsq is not significant, the absence of a specification error is confirmed.

8.4.2 Multicollinearity

Prior to fitting the multilevel model, the possibility of multicollinearity must be examined. Generally in multilevel regression standard errors for the coefficients are large as a result of limited number of respondents at level-2. This is confirmed by comparing standard errors from a standard logit regression and those generated from a multilevel. Lack of collinearity will confirm that the large standard errors is the results of nesting data into groups rather than collinearity between the selected independent variables. To test the collinearity among the nine independent variables used in this study, I will use both the Tolerance and Variance Inflation Factor (VIF) tests. Tolerance gives an indication of how much collinearity that a regression analysis can tolerate; while VIF indicate how much of the inflation of the standard error could be caused by collinearity. If all of the variables are completely uncorrelated with each other (orthogonal to each other), both the tolerance and VIF are 1. If a variable is very closely related to another variable(s), the tolerance goes to 0, and the variance inflation gets very large. Because we have nine independent variables, making each independent variable a dependent variable one at time, we need to run nine regressions[37], such that

$$x_1 = \varphi_2 x_2 + \varphi_3 x_3 + \cdots \ldots \ldots \ldots + \varphi_{10} x_{10} + c_0 + \varepsilon$$

Where c_0 is a constant and ε is an error term. Then the tolerance and VIF for $\widehat{\varphi_i}$ where $i = 1, \ldots \ldots, 9$ with the following formula: -

$$Tolerance = 1 - R_i^2$$

and

[36] The STATA command to test for specification error cannot generate the predicted values from the multilevel logit regression. It can only do that from the normal (non-multilevel) regression results. The same predictors which are statistically significant from the multilevel logit regression results are also significant in the normal non-multilevel regression.

[37] Running OLS with a binary outcome variable will not be problem because multicollinearity is a property of the independent variables, not of the model.

$$VIF = \frac{1}{1 - R_i^2} = \frac{1}{Tolerence}$$

Where R^2 is the coefficient of determination. As moderate multicollinearity is fairly common, a rule of thumb in the literature is that a tolerance of more than 0.1 and VIF of less than 10 is an indication of absence of multicollinearity problem between the independent variables (see for instance, Kutner, Nachtsheim and Neter, 2004). The computed tolerance and VIF are given in Table 9 confirming lack of multicollinearity.

Table 9: Tolerance and VIF measures for the independent variables

Parameter	R-squared	Tolerance	VIF
Direct punishment	0.073	0.928	1.078
Indirect punishment	0.039	0.961	1.040
Income	0.009	0.991	1.009
Social ties	0.012	0.989	1.012
Age	0.008	0.992	1.008
Education	0.031	0.969	1.032
Preferences	0.024	0.976	1.025
Savings	0.012	0.988	1.0124

8.4.3 Goodness of fit

Having confirmed both theoretical and statistical relevance of the selected variables, a need arise to select the best model among several competing models that could fit the data. Two diagnostics are applied to compare full and a reduced model (i) the likelihood ratio test statistic; and, (ii) AIC. For small to moderate sample sizes, it is advisable to use the likelihood-ratio rather than the Wald statistic, as the likelihood-ratio statistic often tends to be larger and gives a more powerful test than the Wald statistic (Agresti, 1999).

The likelihood ratio test statistics compares the change in deviance between a full and a simpler model (with reduced set of variables). We are basically testing the hypothesis that the extra parameters in the full model equal zero i.e. $H_0: \beta_i = 0$ by comparing the full and a simpler model.

$$LR = -2\log\left(\frac{l_0}{l_1}\right) = (-2\log l_0) - (-2\log l_1) \quad \sim \quad \chi_m^2$$

Where

l_0 = maximum of the *likelihood* function when H_0 is true
l_1 = maximum of the *likelihood* function when H_0 is not true
$\log l_0$ = *Log likelihood* value when H_0 is true
$\log l_1$ = *Log likelihood* value when H_0 is not true
χ^2_m = chi-squared distribution with m degrees of freedom (the difference between the number of parameters between the full and simpler model; technically the reason for using -2 times the log of the ratio is that the test statistic has approximately a chi-squared distribution for large samples)

Table 8 shows that when applying the log likelihood test, the p-value generated by comparing the null and the full model is 0.0003, hence rejecting the null hypothesis that $H_0: \beta_i = 0$. This shows that variables included in the full models could have explanatory power on the variations in the repayment behavior. Furthermore, the outcome of the likelihood text confirms results from the univariate analysis which determined the selection of the variable to be included in the statistical model.

Table 10: Information for selecting the "best" model

Tests	**Models**	**df**	LL_i	$-2\mathrm{LL_i}$	**Difference in deviance**	m	**P > chi2**	**AIC**
	Null model vs.	2	-346.577	693.154				697.154
	Full model	11	-324.74752	-649.495	43.659		0.0003	671.495

Given a list of R set of candidate models for the data, the preferred model is the one with the minimum AIC value. That is we wish to find the model that minimizes the information loss, the information loss when a model is constructed to approximate reality. Table 10, shows that when $R = 2$ i.e. comparing between the null and full model, the full model has the lowest value of AIC and can be considered as the best model i.e. the one that has the minimum loss of information when a "true" model is approximated. Therefore, the AIC test outcome confirmed the results generated from the likelihood test.

8.4.4 Results from the statistical models

Variance component model (VPC)

To analyze group differences in repayment behavior, I fitted a basic null two-level *variance components model*, a model with only an intercept and group effects (no independent variables). Two main questions are covered by this model

(i) *How much variation is there in repayment behavior between groups*? and
(ii) *Which groups have particularly low and high repayment rates*?

The estimate of β_0 from the single level logistic regression model is exp(-1.128) = 0.324[38], while it is exp(-1.23) = 0.292 ≈ 0.3 from the multilevel model. This reveals that, by ignoring the consideration of *context* i.e. clustering of the respondents into groups, the standard logistic model has overestimated the average value of the dependent variable i.e. β_0 by about 10 percent, leading into wrongly generating high number of defaulters and reducing the number of those who have repaid on schedule[39]. Hence, failing to consider clustering will lead to ignoring the effects of the c*ontext* in encouraging good repayment behavior.

Table 11: Results from estimated multilevel models

Dependent Variable: =1 if a member has defaulted; = 0 if he/she has paid his loans on schedule.

	Baseline Model	**Null model (VPC)**	**Single-level model**	**Random intercept model**
Parameter	**Equation 1**	**Equation 2**	**Equation 3**	**Equation 4**
Fixed effects				
β_0(Constant)	-1.496	-1.230	-0.838	-1.058
	(0.000)***	(0.000)***	(0.044)***	(0.023)***
Indirect punishments	0.715		0.657	0.662
	(0.000)***		(0.001)***	(0.001)***
Direct punishments			0.633	0.635
			(0.006)***	(0.010)***
Income			0.035	0.073
			(0.860)	(0.724)
Social ties			-0.505	-0.495
			(0.001)***	(0.002)***
Age			0.228	0.318
			(0.256)	(0.138)
Education			0.288	0.294
			(0.234)	(0.262)
Options			0.070	0.128
			(0.758)	(0.601)
Preferences			0.609	0.598
			(0.002)***	(0.004)***
Savings			0.410	0.510
			(0.039)***	(0.034)***
Random effects				
σ_μ^2 (Between-group variance)	0.468	0.477		0.445

p-values in parentheses; significance at 5, 10 and 15% denoted by ***, **, and *, respectively.

In estimating between group effects, we are answering the question, How much variation is there in repayment behaviors between groups? The model estimates are displayed in Table 11; where β_0 is the overall *intercept* and μ_{0j} refers to as group (random) effect or group residuals. The log-odds of groups' members defaulting[40] is estimated as -1.23 when $\mu_{0j} = 0$. Therefore the odds of defaulting for an "average" group ($\mu_{0j} = 0$) is estimated as exp(-1.23) = 0.292. In practice, we would say that the estimated odds of defaulting are generally around 0.3 to 1 and the probabilities are given by 0.292/1+0.292=0.23. This means that the

38 The constant used here is different from the one displayed under equation 3 (Table 8). It is from the single level logistic regression without independent variables.

39 Recall that for a binary dependent variable, β_0 is the proportion of those coded 1 (i.e. $y_{ij} = 1$ for defaulters and $y_{ij} = 0$ for those who have paid on schedule).

40 That is, the log odds when y=1

probability of an individual i in group j to be in a category where there are defaults is 0.23[41]. The assumption that $\mu_{0j} = 0$ means that there is no difference between the mean value of the response variable for group j and the overall mean of the same variable. The intercept for group j is $-1.23 + \mu_{0j}$, which will be higher or lower than the overall intercept depending on whether μ_{0j} is greater or less than zero. To answer the question on how much variation is at the group level, we need to estimate the variance of μ_{0j}. This is given as 0.477[42]. This implies that around 48 percent of the variations in individual members' repayment behavior is attributable to differences between groups. This supports the underlying notion that repayment behavior somehow vary in an important way between groups. It is important to note that, this refers to unexplained variations at the group level without controlling for other factors (i.e. no explanatory variables involved in the model).

Now, which groups have particularly low and high repayment rates? The group effects i.e. μ_j are random variables under the assumption that they follow a normal distribution. Their distribution is therefore summarized by two parameters, the mean (which is fixed at zero) and a constant variance $\sigma^2_{\mu j}$. To compare different groups we need to estimate μ_j for each group. This is done by fitting the model based on the estimates of the model parameters (β_0 and $\sigma^2_{\mu j}$) and the values of the response variable.

Figure 7: Estimates of the group residuals

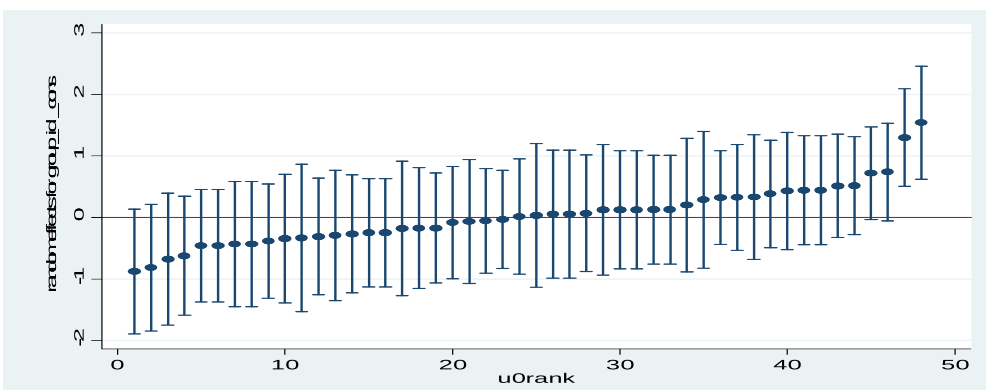

Figure 13 displays group residuals, with 95 percent confidence interval. There are 48 residuals, one for each group. The width of the confidence interval associated with a particular group depends on the standard error of that group's residual estimate, which is inversely related to the size of the sample (Steel, 2008). Here, confidence intervals are quite wide because the sample sizes within some groups are small, leading to larger standard errors

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41 This is the predicted probability for an 'average' group with $\mu_{0j} = 0$.

42 Recall that in the model we are estimating σ_j^2 and not μ_{0j}.

for the estimated group residuals μ_{0j}. Note that a few groups have narrower confidence intervals; these are groups with the largest samples sizes i.e. Seuma and Jitegemee groups. The residuals represent group departures from the overall mean, so a group whose confidence interval does not overlap the line at zero (representing the mean log-odds of defaulting across all groups) is said to differ significantly from the average at the 5 percent level.

In the surveyed groups, only two are found to be on the extreme i.e. defaults rate are higher than the average; in other words, these are groups with the largest positive values of μ_j. These are found at the right-hand side of the plot, meaning that the two groups are the ones with the highest probability of defaulting. However, on the left hand side, there are no groups with mean default rates above average at 5 percent level i.e. no group with low response probability (lowest values of μ_j). Conclusively, this shows that in general most of the groups are around the overall average when it comes to repayment behavior. Lastly, I tested for null hypothesis that group effects do not exists i.e. $H_0: \sigma^2_{\mu_j} = 0$ against the alternative hypothesis of the presence of group effects. The acceptance of the null hypothesis would mean that there are no differences between groups in their mean repayment rates. In other words, we do not need μ_j in the statistical model. The LR test statistic directly given by Stata for testing the null hypothesis as 16.59 with a corresponding p-value of 0.0000 indicating the presence of between group variance and therefore rejecting H_0. Furthermore, this implies that the choice of multilevel approach in assessing variations in repayment behavior is correct. Choosing a single-level model would have not revealed variations at the group level.

Random Intercept Model

Comparison with other models

The results of the random intercept model are displayed in Table 11 (eqn-4). It includes two punishment variables and seven controls. The first group of controls consists of three variables representing socio-economic characteristics of the respondents; while the second group comprises of four variables which might also have some effects on the repayment behavior. Contrary to the single level model (eqn-3), the random intercept model contains group level variance; so it can account for the variations of the repayment behavior coming out of the differences between groups. The multilevel model yields the between group variance as 0.445, meaning that around 45 percent of the variation in the repayment behavior is the result of between group differences, a piece of information not revealed by the single level model. This reflects the realities on the ground, as members' interactions and group characteristics will be different from one group to another. We would therefore, expect behaviors of members in the same group to be similar than behavior of members taken from different groups. What actually the single model has done is to substantively ignoring the importance of the context.

The second notable difference is the underestimation of the standard errors when clustering is not considered. The single level model leads to small standard errors compared to results from the multilevel model. In the case of the single model, standard errors are calculated on the assumption that individuals in the sample provide n independent pieces of information, where $n = number\ of\ obervation = 638\ in\ our\ case$; while when outcomes are clustered (at group level) there will be fewer than 638 independent observations[43],[44]. Compared to other variables in this study, the underestimation is severe in two variables i.e. direct punishment and compulsory savings indicating the possibilities for these variables to be much more defined at the group level.

The third difference is the size of the coefficients. As a result of adding random effects, the coefficients of all independent variables (with an exception of preferences) in the multilevel regression have increased. According to Steel (2008) the increase in residual variance when a random effect is added to the model stretches the scale of the dependent variable meaning that the coefficients β_s will be scaled up[45]. Therefore, coefficients from a random intercept model will be greater in magnitude than coefficients from its single-level version, provided that the distribution of each explanatory variable is the same across groups (Steel, 2008).

The fourth difference is the coefficient of indirect punishment between the baseline equation (eqn-1) and the multilevel model (eqn-4). The coefficient of indirect punishment from the baseline model is 0.715 and it is statistically significant at 5 percent level. It can be noticed that by introducing controls (in the multilevel model eqn-4) the magnitude of the coefficient goes down to 0.662. This suggests quite clearly that a portion of the observed differences in the probability of defaulting is a function of the attributes introduced in the model as controls. The decrease in the size of the indirect punishment coefficient from equation 1 to 4 is 0.053, suggesting that around 7 percent of the punishment gap in the probability of defaulting is accounted by controls introduced in the model.

The fifth notable difference is the between group variance from the null model and random intercept model. In the estimation process, we are actually estimating σ_μ^2 rather than μ_j. The random intercept model yields a between group variance σ_μ^2 of 0.445 compared to 0.477 in the variance component model. This reduction is an indication that the distribution of one or

43 See Steel (2008) for technical explanation on the subject.

44 For those variables at the group level it will mean that we have 48 independent bits of information with which to identify the group effects (while the standard errors calculated for the single level model had 638 independent bits of information).

45 The residual variance in a single level model is $\mathrm{var}(y_i) = \sigma_\varepsilon^2$ while for a multilevel model it will be $\mathrm{var}(y_{ij}) = \sigma_\mu^2 + \sigma_\varepsilon^2$. That's why the residual variance in y_{ij} will always be greater or equal to the residual variance in its single level model. Hence, the increase in residual variance when a random effect is added to the model stretches the scale of the dependent variable leading to scaling up of the coefficients of the independent variables. Level-1 residual variance σ_ε^2 is fixed and can therefore not decrease; only level-2 residual variance σ_μ^2 can change.

more variables varies across groups. As indicated by Leckie (2010), the between group variances between the null and full models will differ because some groups will have higher proportions of members with e.g. higher savings than others etc.

Interpretation of the RIM's results

Significance of the independent variables

The regression result shows that 5 variables are significant at 5 percent level i.e. we reject the null hypothesis $H_0: \beta_{1,\ldots\ldots 5} = 0$ confirming the presence of the relationship between these variables and the repayment behavior. That is to say, there is less than 1 in 20 chances of being wrong in rejecting the null hypothesis. The significance of the direct punishment confirms both the theoretical predictions and empirical findings in several literatures (see the discussion in Section 8). Given the scarcity of literature on the spillover effects of indirect punishments on repayment performance, the significance of indirect punishments in explaining variations in repayment rates adds new information to the existing knowledge on repayment behaviors in economic groups. Lastly, loan repayment behavior is neither related to *age, education*, *other options* and *income*. These insignificances reflect the diversity of results from empirical studies. For instance, while education has been found to have positive influence on repayments (Bhatt and Tang, 2002; De la Huerta, 2010); other studies such as Matin (1997) demonstrates a negative impact of education on one's likelihood of repaying on schedule. In my case, education does not have explanatory power on repayment behavior.

Size and direction of the independent variables

The constant is estimated at –1.058. This is the log-odds of defaulting when $y = 1$, $x = 0$ and $\mu = 0$; then the odds is given by $exp(\beta_0) = 0.347 \sim 0.35.$ That's to say, the odds are 0.35 to 1 that a group member taking loans will default. That means the odds are around 3 to 1 that a group member taking a loan will ***not*** default. In probabilistic terms, this means that, the probability of defaulting is around 1/3rd the probability of repaying on schedule, for all who have taken loans from the groups in which they belong. Saying it differently, the probability of repaying on schedule is three times greater than the probability of defaulting. The general observation here is that other things being equal, the probability of recovering loans in the financial self-help groups is high. However, the x_s are not equal in reality and the inclusion of independent variables and controls would indicate what accounts for variations in the repayment performance.

All statistically significant independent variables have theoretical expected signs. Starting with the fundamental variable i.e. indirect punishment, it can be seen that, everything else being equal, those who have never been punished *indirectly* are about $100\% - exp(0.662) * 100 = 93.90$ percent more likely to default than those who have experience indirect punishments. For the case of direct punishment, those who were not punished for defaulting are 88.7 percent more likely to default than those who have been punished. These results evidence the spillover effects of indirect punishment in addressing repayment problems. In other words, indirect punishments are core aspects of peer pressure in enhancing repayment behavior. In fact, given the sign and the magnitude of the coefficients, indirect punishment is confirmed as one of the important social institutions enforcing compliance on loan repayments. Moreover, its effect on addressing repayment problems is much higher than punishments administered directly on defaulting.

The negative sign on social ties implies that the higher the numbers of friends in the same group the lower the probability of defaulting. This means that forces making social ties contributing positively to repayment rates cancel out the opposite force where social ties lead to deteorating repayment performance. Conversely, to have large amount of shares/savings increases the probability of repaying loans on schedule. In fact, everything else being equal, those holding low number of shares/savings are about 67 percent more likely to default compared to those with large shareholdings in the group. Because savings act like collaterals, having large savings increases the penalty if default occurs; consequently making them (large shareholders) more active in peer monitoring because of the risks of a higher penalty than those with small amount of shares. One of the means to peer monitor is through attending weekly meetings. Results from Section 11.2 confirm that large shareholders are frequent participants in weekly meetings compared with small shareholders. Although my statistical model confirms social ties as a facilitator of repayment behavior, there is need for a separate study that would reveal the diverse and complex manner not only in the way social ties influences cooperation but also how it is built-up once groups are formed and its diverse effects thereafter. The importance of the second part is reinforced by findings from (Wild, Millinga and Robinson, 2008) that group members not only cited social component as more important than the financial gains but also considered that their social status have improved due to their increased wealth and social interactions that group membership confers.

The positive sign on the coefficient of preferences confirm similar results from Bhatt and Tang (2002) and Anthony (2005). That is, if majority of members "prefer" the core service provided by the group i.e. loans, then this may help the group in achieving high repayment rates. In fact, those who are valuing other group services (instead of loans) are 81 percent more likely to default compared to those who give high value to loans provided by the group. While it is not considered as a "sin" to prefer other services instead of loans, it is well acknowledged by group leaders that the core reason for establishing these groups is having access to finance through joint savings and lending. We can then assume that those who value other services will have less interest or motivation to repay compared to those who consider loans from the groups are of high value. To investigate the reason behind giving less priority to loans from these groups, I cross tabulate preferences with outside options to see whether those who did not highly valuing loans are members of other informal financial institutions. The results (appendix 2) show that 77 percent of those who value other services (and not loans) also maintain membership in other savings and credit groups compared to only 23 percent who are not members of other groups**.** This demonstrates that outside options is a proximate reason for them not to value loans higher than other services.

Predictions of the Random Intercept Model

Instead of calculating predicted probabilities for each individual in the sample[46], predictions are made for specific values of x for individuals with certain combinations of characteristics, This is done by holding the group level residuals at its mean of zero i.e. substituting $\mu_j = 0$[47]. The formula is: -

$$\pi_{ij} = \frac{exp(z_{ij})}{1 + exp(z_{ij})}$$

Where z is the linear predictor and is given by: -

$$\begin{aligned} z_{ij} = -1.058 &+ 0.635direct\_pun_{ij} + 0.662indirect\_pun_{ij} + 0.073income_{ij} \\ &- 0.495social\_ties_{ij} + 0.318age_{ij} + 0.294education_{ij} + 0.128options_{ij} \\ &+ 0.598preference_{ij} + 0.510saving_{ij} \end{aligned}$$

First, I computed the predicted probabilities of defaulting by combining two individual experiences i.e. direct and indirect punishments. The second combination involves punishments categories and other characteristics (such as social ties, age etc).

(i) Direct and indirect punishments

The probability for defaulting is only 0.158 when direct punishment exists and members have experienced indirect punishment (Table 12). This means that those who have been punished *indirectly* and have been punished for default in the past are less likely to default. However, the risk of defaulting rises to 0.266 for those who have been punished directly but at the same time they have not experienced indirect punishment. It even goes up to 0.407 for those members who have not received any of the punishment categories. The importance of indirect punishment in addressing repayment problems is evidenced with these predictions.

46 recall that π_{ij} gives the probability of individual i in group j

47 The predicted probabilities obtained will not be the mean response probabilities for the independent variables but rather for the median group (See Steel (2009) for further explanation).

Table 12: Predicted probabilities – direct and indirect punishment

	Direct punishments	Indirect punishments	Predicted probabilities
1	0	0	0.158
2	0	1	0.266
3	1	0	0.261
4	1	1	0.407

(ii) Punishments and social ties

In the absence of direct and indirect punishments: If a member has no friend in the group in which he/she belong and she/he has never experienced indirect punishment, then the probability of default is 0.447, decreasing to 0.231 is he/she has more than 3 friends in the same group (Table 13). For the case of direct punishment, those who have not experienced direct punishment and has few friends the probability of defaulting rises to between 0.470, while for those with many friends it goes down to 0.248. One clear observation is that the absence of both types of punishments increases the predicted probabilities of defaulting especially so in the cases where members have few friends in the groups.

In the presence of direct and indirect punishments: Stronger social ties in the presence of indirect punishment increases the predicted probability of repayment on schedule. In this case the predicted probability of defaulting is 0.134. This is compared to 0.148 probability of default for the case of high social ties and existance of direct punishment (Table 13). In short the existance of direct and indirect punishment greatly reduce the predicted probabilities of defaulting, much more when social ties are strong compared to the cases of weak social ties. Furthermore, the reduction of probability of defaulting is higher in the case of presence of indirect punishment than direct punishments in any range of social ties.

Table 13: Predicted probabilities for– punishments and social ties

			Predicted probabilities	
	Codes for punishments	Social ties	Indirect punishments	Direct punishments
1	0	1	0.294	0.320
2	0	2	0.203	0.222
3	0	3	0.134	0.148
4	1	1	0.447	0.470
5	1	2	0.330	0.351
6	1	3	0.231	0.248

(iii) Punishments and age

In the absence of indirect and direct punishments: Young people are riskier in terms of predicting defaults in the absence of punishment. Their probability for defaulting in the absence of direct punishments is 0.342 compared to the old people which is around 0.275 (Table 14). The predicted probabilities do not differ much in the absence of indirect punishment. It is 0.322 for young people compared to 0.257 for old people. *In both cases, the* *predicted probabilities in the absence of indirect punishments are lower than in the absence of direct punishments.*

In the presence of indirect and direct punishments: However, for those young people who have been indirectly punished, the prediction of defaulting is 0.197 compared to 0.151 for the old people (Table 14). The presence of direct punishment shows that the predictions for defaulting in the future is 0.216 and 0.167 for young and old generation respectively. *Hence, the presence of direct punishment reduce the predicted probabilities of default more than the influence of the indirect punishments.*

I investigated the reasons behind this differential predictions between age group by generating predicted probability using typical individuals combining social ties and age characteristics. *Differences in the stregth of social ties between age groups can explain their differences in the predicted probabilities of defaulting.* For instance, young people who have no friends in the group have a higher predicted probability of defaulting at 0.380 compared to 0.309 for old generation with the same characteristics. Again by comparing the two age groups, even for the case of having large number of friends, the predicted probability for defaulting for young generation is higher at 0.185 compared to 0.142 for the old people. *These results hightlight one of the reasons why young people have higher probabily of defaulting compared to old people. The reason is the limited social connection in the groups making it difficult to peer monitor them.*

Table 14: Predicted probabilities for combined – punishments and age

			Predicted probabilities	
	Codes for punishments	**Age**	**Indirect punishments**	**Direct punishments**
1	0	0	0.151	0.167
2	0	1	0.197	0.216
3	1	0	0.257	0.274
4	1	1	0.322	0.343

(iv) Punishments and preferences

In the absence of direct and indirect punishments: The importance of valuing core service offered by the group (loans) also emerged when predicted probabilities are generated. If a member has never experienced indirect punishments and he/she does not rank loans from the groups ahead of other services, their predicted probability of defaulting is 0.363 compared to 0.238 for those who gave high value to loans offered by the group (Table 15). In the absense of direct punishments, not valuing loans highly than other services give rise to a predicted probability of defaulting at 0.384 compared to 0.255 for those who considered loans are of high priority compared to other services.

In the presence of indirect and direct punishments: If indirect punishments is applied, the predicted probabilities for defaulting goes down to 0.227 and 0.139 for those who did not value and those who valued loans respectively (Table 15). While in the presence of direct punishments the probabilities for default goes down to 0.154 for those valuing loans compared to 0.248 for those who do not value loans from the groups. *Again, when indirect punishments is combined with other individual characetristics (for this case preferences), there is a much more reduction in the probabilities for defaulting compared to those cases where direct punishment is combined with other individual characteristics.*

Table 15: Predicted probabilities for combined – punishments and service

			Predicted probabilities	
	Codes for punishments	**Service**	**Indirect punishments**	**Direct punihsments**
1	0	0	0.139	0.154
2	0	1	0.227	0.248
3	1	0	0.238	0.256
4	1	1	0.362	0.384

(v) Punishments and savings

In the absence of direct and indirect punishments: Those purchasing limited number of shares on weekly basis and have not experienced indirect punishment have a high predicted probability of defaulting at 0.350 (Table 16). It goes down to 0.244 for those who purchases large amount of shares per week. In the absense of direct punishments, those purchasing limited number of shares on weekly basis results into a a high predicted probability of default at 0.371. This goes down to 0.261 for those who purchases large amount of shares per week (in the absence of direct punishment). Again this confirms that non-existance of punishments leads to higher risks of defaults, much more in the absence of indirect than direct punishments.

In the presence of indirect and direct punishments exist: Again in this combination of individual attributes, the importance of indirect punishment in predicting repayment behavior emerge; as whether you buy small or large number of shares per week as far as indirect punishment takes place, the predicted probabilities for defaulting goes down to between 0.143 and 0.217 (Table 16). In the presence of direct punishment, the predicted probabilities for defaulting are between 0.158 and 0.238 for the case of large and small savers respectively. Again, indirect punishments are more effectives that direct punishments in addressing repayment problems.

Table 16: Predicted probabilities for combined – punishments and savings

			Predicted probabilities	
	Codes for punishments	**Savings**	**Indirect punishments**	**Direct punishments**
1	0	0	0.143	0.158
2	0	1	0.217	0.238
3	1	0	0.244	0.261
4	1	1	0.350	0.371

9.0 DISCUSSION

The most interesting finding is the significance of the indirect punishment in explaining variations in repayment performance. As indicated ealier, this category of punishment has been largely ignored in the existing literature which has prominately consider direct punishment as the core element in addressing repayment problems. Indirect punishment is not only significant but also has larger effects than direct punishments. The prominance of indirect punishment might be the result of the way groups are structured. As mentioned earlier, at the beginning members jointly save for 11 consecutive weeks and thereafter lending operations start to materialise. Only indirect punishments take place during these said 11 weeks. Therefore, the seriousness in enforcing compliance is firmly set during those 11 weeks. That is to say the frequencies of indirect punishments would scare potential defaulters when lending start. In other words, if groups frequently punish (even for small offences), then potential strategic defaulters would believe that penalties for defaulting will be more severe, and this peer pressure would enforce repayment on time when lending start.

The significance of indirect punishments in enforcing loan repayment reappear again when predicted probabilities are computed. With an exception of age, in all combinations (the combinations between punishment categories and other chacteristics e.g. savings, social ties etc), the predicted probabilities of defaulting are less in the presence of indirect punishments than in the presence of direct punishments. In other words, in the absence of direct punishments the probabilities of defaulting are higher than in the absence of indirect punishments. In this case, if the group does not punish indirectly, then it has no chance to be sustainable. As in many literature social ties emerge as an important aspects in explaining repayment behavior. Its significance is mainly seen in terms of age categories of members. In particular, young people have higher proibabilities of defaulting because of the limited social connections they have in their groups, making it difficult for other group members to monitor them, to control strategic defaulting. The policy treatment here is not to "isolate" young people from collective actions but to ensure that social ties are strong before groups are formed in order to facilitate effective peer monitoring.

As expected, compulsory savings is positively influencing repayment performance. Its importance is not only in terms of acting as collateral but also one of the incentives for members to undertake peer monitoring. This is because of the way groups are structured i.e. members are owners and they get profits at the end of the round (with profits depending on interest income generated from loans). That means if members default, large savers have more to lose in terms of expected profits (which is distributed based on the number of shares). Therefore peer monitoring will be undertaken oftenly by large savers compared to small savers large savers have mre to loose than small savers. We have seen that big savers are good cooperators not only in terms of repayment behavior but also in terms of meeting attendance compared to low savers. That means "attending meetings" is one of the mechanism through which large savers undertake peer monitoring.

Methodologically, we have also seen the appropriateness of adopting multilevel modeling when data are clustered at different level. The magnitude of the between group variance in the variance component model supports the inclusion of the random coefficient modeling. In reality, the between group variance reflects differences in the ways in which these groups are managed, the way members interact, internal social dynamics as well as the way groups associate with the outside world. All of these might have some effects on individual repayment behavior. For instance, in terms of instituting punishments, there are groups with "an active" disciplinary officer compared to others; while in other groups that role is performed collectively i.e. everybody monitor everybody. These differences might have some partial effects on individual repayment behavior. Even members' motives for establishing groups differ. Apart from savings mobilization and the production of collective good (loans), some groups have different primary motives behind their formation. There are groups which have been formed by widows and/or people living with HIV etc. During general discussions with leaders of these types of groups, they prefer to be lenient to defaulters differently from groups in which savings and loans are primary motives. Another group level factor is the role being played by CBT. Frequency of visits by community trainers differs between groups. Some groups are visited more often than others, either because of trainers residing near the location of the groups or because of the group willingness to pay for the training fees or in other cases trainers are themselves members of some of these groups. These groups are expected to performance well in terms of debt repayments, punishment and other joint activities. The main reason being is the complimentarity between external monitoring (community trainers) and internal peer monitoring. All these are group level variables that accounts for the presence of the between group variance.

10.0 CONCLUSION

Findings from this study add three vital elements in the existing literature. First, indirect punishments also account for variations in repayment behaviors; hence, ignoring its effects will misinform policy initiatives on means in which economic groups can be sustained. Second, in relation to the first is the need to disentangle punishment categories when investigating factors working for or against collective groups. Third, indirect punishment can produce even larger effects on addressing repayment problems than direct punishments. These results provide an avenue for further research in four separate areas. First, is to go beyond the random intercept modeling and apply a random slope model that would reveal whether both the intercepts and slopes vary randomly across groups, for instance, for some groups, an independent variable can have a large effect on the log-odds of the probability of defaulting while for others it might have a small effect. Another avenue is to include in the model specific contexual variables (at level 2 and 3) allowing for their influence on individual repaymet behavior to be measured. Third, a need for further research on understanding what drives indirect punishment to have a positive impact on repayment behavior. An experimental approach might be appropriate as far as the laboratory games are structured in a way that captures the salient features of the financial self-help groups. Forth, the ultimate goal of any economic activity such as lending in financial self-help groups is income generation. Therefore, there is an avenue for future studies to investigate the impact these groups have on improving livelihood of their members.

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APPENDICES

Appendix 1: Cross tabulation: REPAY and indirect punishments

REPAY	Indirect punishment		
	0	1	Total
0	342 70.95%	140 29.05%	482 100.00%
1	85 54.49%	71 45.51%	156 100.00%
Total	427 66.93%	211 33.07%	638 100.00%

Appendix 2: Cross tabulation: Other options and preferences

Preferences	Other options		
	0	1	Total
0	315 76.95%	97 23.54%	412 100.00%
1	174 76.99%	52 23.01%	226 100.00%
Total	489 76.65%	149 23.35%	638 100.00%

Appendix 3: List of the surveyed groups and number of respondents per group

No.	Group name	Respondents	No.	Group name	Respondents
1	Mshikamano	15	25	Jahazi no. 1	18
2	Umoja	7	26	Odefu no. 2	8
3	Mandela	20	27	Odefu no. 3	4
4	Maarifa	17	28	Odefu no. 1	13
5	Matumaini2	7	29	Mboga mboga	19
6	Jitihada	19	30	Nufaika-yombo matangini	12
7	Bwawani	15	31	Bahati group	6
8	Ebeneza	13	32	Gezaulole	17
9	Mshikamano	13	33	Jukuila	8
10	Upendo	15	34	Kiwawama	8
11	Neema - matankini	14	35	Tusonge mbele	16
12	Seuma	23	36	Urafiki	5
13	Matumaini1	9	37	Mshikamano	17
14	Neema	19	38	Upendo	15
15	Amkeni	12	39	Upendo no. 91	10
16	Tupendane	10	40	Amka	15
17	Ukweli na uhakika	17	41	Maendeleo matangini	15
18	Hatushindwi	14	42	Juhudi na maendeleo	12
19	Tembo	10	43	Umoja ni nguvu	11
20	Jt segerea	17	44	Tunaweza no. 65	4
21	Jitegemee-183	22	45	Umoja matangini	15
22	Tujikomboe-114	19	46	Nguvu kazi - matangini	19
23	Amani no. 135	11	47	Tupendane	11
24	Amani group no. 59	12	48	Tujitambue	10