Repayment Performance of Joint-Liability Microcredits: Metropolitan Evidence on Social Capital and Group Names

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ABSTRACT

This study empirically tests the predictions of four primary theories applicable to joint-liability microcredit programs' repayment performance using an administrative data in a metropolitan setting. We introduce a new variable -group names- as a proxy for social capital to capture cooperation, solidarity and drive for success, which shows a significant positive impact of 9.9% on repayment performance. Precise calculations of residential distance between group members show a deterioration of repayment performance by 1.1% with a 15-minutes increase of minimum walking distance. The results also show that joint liability, sectoral diversification, type of sector that the borrowers facilitate, the ratio of new members in a group, characteristics of loan officers, loan amount, interest rate, income-loan amount coverage ratio, the existence of senior members, average education and diversity in income streams significantly affect repayment performance.

JEL classification:

G21 – Banks, Depository Institutions, Micro Finance Institutions, Mortgages

D71 - Analysis of Collective Decision-Making (Social Choice, Clubs, Committees, Associations)

O12 - Microeconomic Analyses of Economic Development

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1. Introduction

Microfinance Institutions (MFI) provide credit to poor entrepreneurs, financially excluded from traditional banking primarily due to lack of physical collateral. Originally, microcredit programs were seen as successful mainly for the attribute of self-selection while forming groups and the interdependency created through joint-liability for repayment (Ghatak and Guinnane 1999); -leading to utilization of local information to the benefit of the lender, minimizing asymmetric information problems; i.e. adverse selection and moral hazard. Microcredit replaces the missing physical collateral of conventional banking with social collateral; utilizing social capital, local information, peer support and pressure when required (Besley and Coate 1995; Armendariz 1999). Later, among the older and more established MFIs, although there has been a shift to lending on an individual basis, MFIs still draw on groups with various devices to incentivize groups members to monitoring their fellow group members. So, groups are seen as key component in building social capital and the norms which lead to microcredit success (Halder and Stiglitz, 2016).

It is not surprising that joint liability lending has emerged and is still widely implemented in the less developed and rural settings worldwide, with unexpectedly high repayment rates compared to traditional banking institutions (Hermes and Lensink 2007; Cull et al. 2007). Being characterised by strong and intimate social ties, immobility and close proximity of residents who are homogeneous with regards to educational and occupational experiences, economic and entrepreneurial activities; rural settings are clearly environments that facilitate screening and monitoring which constitute the cornerstones of the microcredit programs. The threat of social sanctions is more credible in small village communities and amongst people who have strong social ties relative to urban/metropolitan environments where such ties are weaker. Communities in metropolitan areas may also be less concerned about reputation as an asset and therefore the credibility of social sanctions may be lessened. In urban/metropolitan areas local information networks and information flow may also be more fragmented obstructing mechanisms for screening and monitoring. Previous microcredit studies and the wider literature from sociology has recognized these rural-urban differences (Ghatak and Guinnane 1999; Morduch 1999; Armendariz de Aghion and Gollier 2000; Kugler and Oppes 2005; Postelnicu et al. 2018; Fischer 1982; Tönnies 1970).

Earlier research findings do present limited evidence that the relative strengths of the mechanism affecting repayment performance may differ in rural and urban settings. Wydick (1999) explored group lending in Guatemala, both in an urban and rural context. His results showed that in rural areas borrowers were aware of each other's weekly sales, and it was the willingness to apply social pressure for rural groups that was the driving force behind better repayment performance. In contrast, for urban groups, greater distances between group members were found to obstruct monitoring ability and in this context repayment performance was improved via *intensive monitoring* and *intra group insurance*. Paxton et al. (2000) investigated two locations: rural villages and larger towns in Burkina Faso. The authors found that rural borrowers have a higher dependence on agriculture, which brings a higher degree of *income variation, risk* and *covariant incomes*; resulting in higher covariant risk (similar to the finding of Zeller, 1998). The repayment performance is lower for *homogeneous* groups in terms of economic activity, occupation and income. Related to this, they noted that groups in urban regions, where the financial landscape is sophisticated, record a better repayment performance. More recent studies present evidence in rural-urban context from Eritrea (Hermes et al. 2005, 2006) Thailand (De La Huerta 2010), Bangladesh (Khandker 2012), Mexico (Postelnicu et al. 2019) and in urban context only from Peru (Karlan 2007), Mexico (Griffen and Husted 2015) and Jordan (Al-Azzam et al. 2007, 2012, 2020) particularly linking repayment performance to social capital using different proxies for social ties within the groups.

In this paper we use administrative data from a leading metropolitan MFI in Turkey to find out the factors affecting joint liability repayment performance of borrowing groups. This adds to the limited microcredit literature focused on metropolitan areas, exploring how microcredit can work in areas characterized by weakened interpersonal relationships; more fragmented local information networks; less proximity between members; higher mobility; often-insufficient credibility of social sanctions; and finally, greater diversity in economic activities and business models. This study also provides the first evidence on microfinance repayment rates for Turkey, an important dynamic emerging economy, one of the top 20 most populous countries in the world with a population of over 84 million people.

In addition, our research provides novel evidence on the impact on repayment rates of social capital which reflects the group's vision, values and common identity, part of which may have been formed during the group formation process. As Halder and Stiglitz (2016) argue the building of social capital and norms within groups (beyond those simply supported by economic incentives) is important in explaining microcredit successes. Typically, the measurement of group social capital has focused on variables capturing ties between group members, and social "closeness" and the similarity between members prior to group formation. The evidence on the relationship between these measures of social capital and microcredit repayment success is mixed (see the review within Al-Azzam et al., 2020). Social capital though is also likely to be created more dynamically during group formation. Drawing on pre-existing social capital, individuals are likely to self-select into groups with common values. However, the process of group formation itself and the interactions required in this process are likely to shape the group's vision, values and identity, and may be less related to the measures of prior social capital. In urban settings, the larger initial heterogeneity of group members might also be expected to lead different group formation dynamics in terms of how well a common group vision and identity is created. Social capital formed in this way may also be self-reinforcing with groups potentially more able to develop “a meaningful social identity before the economic calculus enters the picture” (Halder and Stiglitz, 2016). This type of social capital is also likely to affect traits such as group cohesiveness and commitment which may be partially observable and used as a signal of quality by MFIs, potentially affecting how the group is treated, for e.g. in terms of its access to future loans.

We explore this in the available data using information on the unique name chosen by the group members to represent their group while applying for the loan. Using this information, we construct an indicator which we argue captures part of this unobservable social capital reflecting group dynamics such as cohesiveness, initial commitment, and willingness to monitor/be monitored by other group members. We propose that more success-oriented groups are more likely to pick names containing strength and togetherness. Although missing so far from the microcredit literature, the wider social and economic evidence shows that names reflect identity, can strengthen bonds, (but possibly differently depending on the process of name choice). Names also vary systematically with other characteristics, and are associated with a variety of economic outcomes. As Fombrun (1996) states an individual’s name is a powerful symbol that define who we are and what we can become. The name chosen by parents for their child is in part a symbolic expression of parental expectation and cultural and wider identity (Finch, 2008; Bush et al, 2018). In addition, evidence from psychology suggests that the process of choosing names is influenced by the ability of those involved to create clear sense of themselves in future (Zittoun, 2004). A name can also create a sense psychological ownership (Sarstedt et al., 2017). The evidence also shows that individual names carry information, being systematically related to characteristics such as parental income, education, values and lifestyles (Bloothooft and Onland, 2011). There has also been extensive research on the role of names in corporate identity and branding drawing on institutional theory (Schmeltz and Kjeldsen, 2016). For example, Glynn and Abzug (2001) provide evidence that an organization's chosen name reflects key features of its organizational identity and legitimacy. The use of eponymy, firms being named after their owner or the family, has been shown to be linked to improved firm performance, and the values and identity of the firm (Zellweger et al, 2011; Belenzon et al, 2017). There are wide of range of studies showing how corporate names and in particular name changes are used as a signal of firm quality, affecting market valuation prices and transaction volume (Agnihotri and Bhattacherya, 2017; Cooper et al., 2001; Cooper et al., 2005; Lee, 2001; McDevitt, 2014). In the microcredit context, this literature suggests that the group name chosen is likely to contain information on unobservable characteristics and social capital within the group, and hence potentially may signal differences in quality of borrowers in terms of diligence, success and repayment capacity. The process of group formation which includes choosing a name for their group reflecting themselves can create psychological ownership and improve the sense of togetherness, possessiveness, strengthening the bonds in a group.

The available administrative data set from the leading Turkish MFI, provides a rich set of information allowing a wide range of factors found to be important in repayment rates to be considered. To guide our empirical analysis, we draw on the theories on group lending by Stiglitz (1990); Banerjee, Besley and Guinnane (1994); Besley and Coate (1995); and Ghatak (1999) within the framework developed by Ahlin and Townsend (2007). This allows us to explore the impact of the group name indicator and other factors within a recognized framework.

The results show controlling for all other factors, that the group name measure has consistently large positive and statistically significant effects, with the expected probability of paying on time increasing by 9.9% for groups that chose names suggesting cooperation, solidarity and determination compared to groups without such featured names. There is also evidence that group performance improves where the within group hierarchy is stronger, e.g.

when there is an older member in a group. Weaker links between group members reduce repayment performance with a fall in prepayment probability of 1.1% with a 15-min increase in the minimum walking distance across group members. The broader results also add new evidence on the roles different factors play in a metropolitan setting and how they link to the different theoretical predictions (Ahlin and Townsend 2007). For example, we show that loan size has a non-linear effect on repayment performance acting negatively on repayment at low loans amounts but positively when amounts are higher.

The rest of the paper is organized as follows: Section 2 briefly presents the theoretical framework and the tested predictions. Section 3 delineates the institutional setting, Section 4 describes methods and data, Section 5 presents the empirical results and Section 6 concludes.

2. Theoretical Framework

Typically, in joint-liability microcredit programs, individuals with different risky projects come together and form groups to apply for loans together. The MFI approves loans to selected borrowers for their projects but the whole group is held responsible for a group member's repayment failure. If the group cannot repay the loan because of the defaulting of their peers, the entire group will lose its right to access follow-up loans at increased amounts. Thus, jointly liable microcredit groups induce individual borrowers to use the local information buried in social networks to the improve loan repayment in MFIs. More explicitly, borrowers use their social ties to screen potential peers, monitor each other's actions and impose social sanctions to enforce repayment commitments. These features help to overcome the asymmetric information problems of a regular microcredit contract.

Table 1 - Model predictions

As a theoretical framework, we use a unified foundation proposed by Ahlin and Townsend (2007) summarized in Table 1 to frame the empirical strategy used. Each model in

Table 1 introduces a different mechanism to overcome asymmetric information problems in standard loan contracts. Ghatak (1999) emphasises the importance of assortative matching processes during screening when dealing with the *adverse selection problems*; and other models focus on the importance of monitoring in overcoming *moral hazard problems* that occur *ex-ante* (Stiglitz 1990; Banerjee et al. 1994), and *ex-post* (Besley and Coate 1995). Ahlin and Townsend (2007) theoretically contributed to these models and explored each of these determinants, incorporating additional variables. After herein, where relevant, Banerjee et al. (1994) is referred as BBG, Besley and Coate (1995) BC, and Ahlin and Townsend (2007) AT.

The non-highlighted areas in Table 1 show the original theoretical model predictions, with the highlighted areas showing the predictions based on AT extensions. For example, interest rates and loan sizes were the key variables in the original model of Stiglitz. In their extension, AT introduced correlation of returns, degree of joint liability and cooperation among group members, productivity enhancement measures to the model and showed how these variables impacted on repayment rates theoretically.

Some explanatory variables are standard across all models and have similar predictions, e.g interest rates. In a number of cases, the models have predicted effects which are unique. For example, only the Ghatak model estimates the effect of screening on the repayment performance. Similarly, penalties (both official and unofficial) are considered only by BC, while the cost of monitoring is a focal variable only in BBG. For a number of factors, the models predict different impacts. For example, for cooperative behaviour, the predictions differ. While Stiglitz predicts that it increases performance, associated with BBG and BC, repayment is predicted to decline with cooperative behaviour.

The empirical estimation discussed below is a reduced form approach but draws on the theoretical predictions in several ways. First, they provide the basis for the types of variables which should be included in the analysis. Second, the predictions provide the framework through which the results can be judged and interpreted. This is useful for guiding the discussion of the results and even, as is often the case, where a variable in the empirical analysis may potentially have an impact via a number of mechanisms identified by the theoretical models.

3. Institutional Setting

In order to explore the predictions, we use data from a Turkish MFI, MAYA, which operates in Turkey's industrialized Istanbul metropolis. The data consists of the monthly repayment history 285 loans from 2003 to 2007, linked to 211 female-only borrowing groups.

The primary mission of MAYA is to provide micro loans to low-income female entrepreneurs to support them in launching new business ventures or in developing their existing ones. Many of the features of the program are similar to that of Grameen and other MFI operations around the world, although there are a number of differences to the classic Grameen model to fit the requirements of the metropolitan environment.

Micro loans were provided based on joint liability to self-selected small solidarity groups (3-10 people). Typically, group members live close and knew each other before forming the groups. MAYA communicates with the borrowers face to face during the application, evaluation, approval and monitoring processes. It is seen as crucial for the applicants to attend several meetings before credit is distributed. In these meetings the loan officer explains how the system works and training is provided which is important in preventing arrears in payments. In most cases borrowers come to these meetings with pre-formed groups, but if not, borrowers are introduced to each other, informed about their businesses and form their groups. Initially it was not permitted for the relatives to be in the same group (to reduce collusion risk and increase risk diversification). Reflecting the specific challenges of group formation in the metropolitan environment, this restriction was lifted after borrowers' complaints about the difficulty of finding suitable partners.

Although borrowers in the same group can borrow loans of different amounts, the number of instalments is identical for all members of the group – ranging from 4 to 12 months. The institution does not have a rule for the differentiation of the loan sizes within a group but considers the repayment capacity of the individual borrower to determine the loan amount. After determining the repayment capacity of the borrower, the loan officer offers a loan amount to the group with a credit options list (including the combinations of the maturity term of the loan, interest rate and loan amount). It is then up to the group members to decide the most appropriate combination for the group, including the number of instalments payable. In case of a good repayment history a new loan up to 25% more than the previous loan amount is accessible the day following the last instalment date of the loan. When a loan is not paid, the loan officer initially tries to obtain the unpaid amount from the non-paying borrower (with both official and unofficial sanctions), but if she still does not pay it is the responsibility of the group to pay it from its own resources. If the group is not able to repay the loan because of the peers' default, the entire group loses its right to access these follow-up loans. Groups with borrowers who pay late are charged with penalty fees that are 30% more than the current loan interest rate.[1]

The group members, who do not repay regularly, do not attend meetings, misuse loans, sub-lend, do not support the others when repaying, or provide inaccurate information when applying can be removed by the group. In cases of frequent disputes within a group, the borrower can be moved to another group if the new group's members also confirm the transfer. There may also be dropouts from the group due to other reasons such as the family moving to another city. The groups can welcome new members once all the repayments are completed.

In the classic Grameen model, attending group meetings and monitoring the activities of the group members is a core feature. However, this is more difficult to achieve in a

[1] The penalty charged is calculated as follows: *Unpaid loan amount * number of days * 30% more of yearly interest rate / 3600*.

metropolitan setting. In the MAYA program groups and officers try to meet regularly but due to the limited number of field officers and challenges associated with the mobility within the city (traffic congestion, distance, high transportation costs), meetings are relatively infrequent compared to rural microcredit programs. Any borrowers having repayment difficulties are phoned either daily, or on alternate days by the loan officer to encourage repayment. If the repayment of an instalment is late, the loan officer immediately calls the contact person of the group to investigate the reason. Then, all the other group members are notified and their responsibilities are reiterated. In cases of partial payments, the same procedures apply. Similarly, in the classic MFI scheme, instalments are paid weekly and collected by the loan officers in public whereas in MAYA, both the lending and repayment of loans take place via internet banking, bank branches and ATMs, with instalments paid *monthly*.

4. Methods and Data

Empirically, we aim to explore how the repayment performance varies across groups with different loan and borrower characteristics, using the predictions in Table 1 to frame the analysis. Table 2 provides an overview of the information used in the empirical analysis. The dependent variable shows the group's repayment performance and is calculated as to whether the group has ever paid any penalty during a repayment term or not. We model the probability that a group has not paid a penalty estimating standard logit and mixed logit models with a set of independent variables, which reflect group- and loan-specific characteristics. The models are estimated using maximum likelihood. A full list of independent variables used and summary statistics are given in Table 2. Below, we describe the construction of the dependent and independent variables used. We have classified each variable in terms of its primary effect in relation to the different theoretical effects identified in Table 1. As discussed in Section 2, these are not one-to-one mappings and some variables may also measure elements from the other categories identified in Table 1. Nevertheless, they provide a useful gauge to against which to interpret the results.

Table 2 - Variable Descriptions and Descriptive Statistics

Consistent with the above the binary dependent variable (*GNO_PENALTY*) is defined as equal to 1 if none of the group members had been charged a penalty for the late or partial payment of the instalments, and 0 otherwise. As reported in Table 2 on average, 22.81% of the groups has never been charged a penalty for late repayments.[2]

Three of the theoretical models predict that the degree of joint liability affects repayment performance. We use the variation in loan shares as a proxy for the degree of joint liability in a group and define the variable *JOINT_LIABILITY* which takes the value 1 if the loan is distributed equally among borrowers, 0 otherwise. Table 2 shows that 53.68% of the groups shared the loan equally.

To capture the correlation of risks within the group (Sadoulet, 1999; Ahlin 2009), we construct a number of measures. First the borrowers' sectors were organised into 11 main (NACE) groups. The data shows that 60.2% of the borrowers deal with trade related businesses whereas 32.1% are in manufacturing. The remaining 7.7% mostly activate in "Arts, Entertainment and Recreation", "Accommodation and Food Service Activities" and "Administrative and Support Services". The first proxy, *SECTOR_DENSITYX,* is generated to measure the concentration of members in the same sectors, it is equal to 1 if all the members in the group are in the same sector and 0 otherwise. Secondly, two more variables are generated: One is *TRADE_PROP* which shows the ratio of borrowers engaged in 'trade' (Wholesale and Retail Trade) related businesses in the same group, the other is *MANUFACTURING_PROP*

[2] Rather than reflecting the 'written-off' loans, the dependent variable indicates 'payment with an arrear', as the figures on annual loss rates of MAYA show that almost all groups sooner or later repay their loan. Our dependent variable considers whether any of the group members has ever been charged penalty due to paying with an arrear. Even one member in a group has been charged a penalty of a small amount, the whole group is considered as paid with an arrear.

which is the ratio of the borrowers involved in “Manufacturing” businesses in the same group. The final measure here assumes that the variation in the incomes of the borrowers is reflected in the variation of sectorial indexes. Using data from the Istanbul Stock Exchange Market (ISE) we build an index for returns.[3] And then we consider how far the indexes have changed over a two-year period. The variable *SYMMETRIC* takes the value 1 if the sectorial shocks hit the group members simultaneously (either positively or negatively) and 0 otherwise. Table 2 shows that 63.51% of the groups were hit simultaneously. All other things remaining equal, we would expect this variable to affect repayment performance negatively if there has been a macro level shock affecting the groups negatively, and positively if otherwise.

As mentioned in the introduction, the institutional data provides novel information on group names chosen by the members. Before applying for the loan each group is required to decide on a unique name to represent themselves. The names chosen by the groups may be indicators of their ex-ante intention, determination and consciousness for success, cooperation and solidarity. While the majority of the groups choose common names; e.g., colours, singers, songs, districts and animal names; some groups have chosen names containing characteristics of ambition, success and solidarity. Among them are Women Solidarity, Amazonians, Xena, Collective, Ambition, Team, Aim, Professionals and Street Combatants or names that reflect support, friendship and awareness of team spirit such as Companions, Golden Girls, Ours, Three Buddies, Friends, The Bees, Three Stars, Three Sisters, and Confidantes. A variable *GROUPNAME* was constructed using this information, taking value 1 if the chosen group has these elements in its meaning and 0 otherwise.[4]

For the cost of monitoring in a group, we use walking distance across group members, where the closer the members live to each other the lower the monitoring cost.

[3] An example of variable construction is presented in the appendix Note 1 and Table A1.
[4] A full list of team names is provided in the appendix Table A4.

MIN_DISTANCE describes the time length of walking (in minutes) across group members who live the closest and *MAX_DISTANCE* shows the time length of walking (in minutes) across group members who live the most distant to each other.[5] Although the average minimum walking distance of 23 minutes (Table 2) is relatively short in a metropolitan context, it is still relatively long for daily checks on other group members. Partners chosen from more distant locations (such as 300 minutes) may indicate the difficulties in finding a reliable partner nearby. Drawing on home addresses available in the administrative data, it was possible, through Google Map® to precisely determine the exact walking distances between the borrowers' residential addresses.[6] The potential costs of monitoring within groups is also captured via *WORKING_OUTSIDE*, the dummy equals to 1 if the majority of the borrowers are working outside at publicly observable places like a stall, store, bazaar or workshop. Here, we assume that those borrowers who work at observable places can monitor each other's effort, thus we expect that groups with majority of borrowers working outside perform better due to improved monitoring. Lastly, *GROUPSIZE* (i.e. the number of borrowers in the group) is used as a measure which should also affects monitoring, with effective monitoring more difficult in larger groups. However, counterbalancing this more members in the group may work as an *insurance effect* related to the correlation of returns within the groups.[7] The Table 2 evidence suggests however that smaller groups are preferred by borrowers consistent with the monitoring cost interpretation, i.e. even though groups of up to 10 borrowers are allowed, average group size is 3.26 borrowers.

[5] The distance variables, categorized under *cost of monitoring*, can be used as a proxy for *screening and cooperation* as well. Namely, the group members who live close to each other are more likely screen each other before constructing jointly-liable loan relations and may be more likely to cooperate. Similarly, borrowers who live far from each other should have done the screening *ex-ante*, at some point before loan relations. Thus, rather than choosing less reliable partners living close to them, it maybe that the borrowers may opt for partners whose solidarity and reliability have been tested at some other platforms (such as kinship).

[6] Figure A1 in the appendix show an example of calculations on Google Map for close and far distances.

[7] Thus, alternatively the variable GROUPSIZE can also be used as a proxy for *covariance.*

The available variables specifically associated with screening are limited in the data. We assume that screening (and monitoring) of fellow group members is easier if members work in similar occupations as they can better understand the quality of the work and earning potential of their fellow group members. Of course, if group members are concentrated in a single occupation this may reduce the risk diversification within the group. The data shows that the borrowers' earnings are spread across sixty occupations. Based on this information, for each group, we identified the ratio of the borrowers dealing with same types of businesses, to construct the variable (*OCCUPATION)*, which is the ratio of borrowers within the group in the same type of business.[8]

We also constructed a dummy variable *NEW_MEMBER* which equals 1 if there is at least one member that joined the group in the later stages. Here, in line with Ghatak (1999), we assume that existing members will screen new entrants and only allow borrowers who are less risky than the group's overall risk level to join. We also use an alternative definition, *NEWMEMX*, which shows the ratio of the new members in the group. Lastly, we use the variable *DRELATIVE* which equals 1 if the groups have at least two borrowers with identical surnames and 0 otherwise. Existence of relatives in a group can either improve or deteriorate repayment performance, Table 2 shows that in 21.05% of the groups, there are possibly relatives within the group.

Regarding official penalty, the first proxy we considered is the loan officers who are crucial throughout the repayment process, ensuring that borrowers do not misuse the loans and do repay it back regularly. The data shows that 95% of the groups are followed by two officers: Officer-F and Officer-Y. The dummy *OFFICER_F* equals 1 if the loan is under the supervision of Officer-F and 0 otherwise. Similarly, the dummy *OFFICER_Y* equals 1 if the loan is under

[8] The *OCCUPATION* variable categorized under *screening*, can also be used as a proxy for *cost of monitoring* assuming that the borrowers dealing with the same type of businesses can more easily monitor and get information about how well their peers' businesses are doing.

the supervision of Officer-Y and 0 otherwise. Depending on the penalties and pressure applied, we expect loan officers to influence the repayment either positively or negatively. As a proxy for *unofficial penalties*, we regarded differences in terms of trait of borrowers, such as age, education and income. It is assumed that the larger the age difference, the more influential is intra-group pressure, hierarchy and group discipline. In line with this, we considered that, it may be easier and more effective to apply sanctions when there is a senior member in the group. The variable *AGE_SANCTION* takes value 1 if the age difference between the oldest and youngest member of the group is more than 25 years. Also, when borrowers are all the same age, the warnings may be of less consequence as the relationship may be more informal. To capture such effects, we use the variable *AGE_DIFF*, which is the standard deviation in the group members' ages. Income and educational differences of the borrowers may also lead to a higher degree of hierarchy in the typical relationship within groups which in turn may lead to improved ability of those at the top of the hierarchy to socially sanction other group members. Differences in income may impact in other ways too as if there is a member with significantly higher income than other, they may be more able to compensate for any defaulting partners. We expect all these variables capturing age, income, and educational differences to improve repayment rates.

The level of education of the borrowers is regarded as a productivity shifter. Using the information on the formal educational achievement (*degrees*) for each borrower, *AVE_EDU* is constructed through calculating the average years of education for the group. The other proxy that can create an incentive and pressure on the borrowers to be more productive can be the number of dependents they are responsible for. The variable *DEPENDENT* shows the average number of dependents in a group. However, as many dependents may impede productivity, this effect may be non-linear so that we also include the square of this term (*SQDEPENDENT)*

We also include a set of variables on contract terms which are common in empirical specifications in the literature (Sharma and Zeller 1997; Godquin 2004; Al–Azzam et al. 2012), namely, loan size of the group (L) and the interest rate of the loan (r). *LAMOUNT* shows the size of the loan for the whole group and *SQLAMOUNT* is its square. Loan amounts are not high in the beginning as a precaution, but over time, as both sides come to know each other better, the loan amount increases. The theory suggests two competing processes at work and therefore both the level and its square are included in the model. First, we expect that the probability of default increases as the loan size gets larger. As it becomes harder to bail out the defaulted borrowers as the loan size increases, repayment performance may worsen (a negative sign). On the other hand, the existence of penalties (both informal and formal) may make members more cautious not to default or be supportive to partners in times of delinquency. Moreover, the lending institution may put more effort into screening and monitoring as the loan amount increases.

The variable *TINT* shows the annual interest rate charged on the loan. In general, MAYA provides credit to the groups at a uniform interest rate basis. The interest rate is determined by averaging high street bank rates, taking disbursement fees into consideration, and is updated every 3 months. Table 2 shows that the interest rate is 56.68% on average with a variation of 49.14% to 62.88% per annum. We also used an additional variable which is generally considered by banks to screen loan applications in traditional banking, i.e. the ratio of income to loan, *LAMOUNT_INCOME*. We expect as this ratio increases, the repayment rate improves.

Finally, since it is more likely for groups with a longer loan term to encounter repayment problems owing to being exposed to risk over a longer time period, we included *LOANTERM* in all regressions as a dummy for each loan term. Also, we controlled for the group age and how many loans the group has taken before, i.e. loan cycle.

One concern with the use of the range of explanatory variables included is the potential risk of high correlation between two or more predictors in our regression, and the associated multicollinearity, which may mean the estimated coefficients are sensitive to small changes in the model, affecting standard errors and the precision of the estimated coefficients. In order to identify the extent of this the correlation matrix and the variance inflation Factors (VIFs) have been calculated (Mansfield and Helms 1982) (see Table A2 and A3 in the appendix). These results indicate that generally the levels of correlation between the variables are not particularly high. More formally the VIF results indicate that apart from the structural multicollinearity (because of squared terms), VIF values are less than 5, again suggesting that multicollinearity should not play a critical role in the results. As is reported below we also explore this informally by estimating a range of specifications to ensure the results are robust to the inclusion/exclusion of sets of (insignificant) variables.

5. Empirical Results

The results of the logit[9] and mixed logit modelling of how explanatory variables impact on the joint-liability repayment probability are summarized in Table 3. Further specifications to illustrate the robustness of the results to the inclusion/exclusion of various sets of variables are included in Table A5 in the appendix.

Columns (1) to (6) in Table 3 present the specifications used in the regressions, Column (6) being our preferred specification. Column (7) shows the marginal effects of each variable using the specification in (6), Column (8) shows the odds ratios and Column (9) is the multilevel mixed effects logit results associated with the preferred regression. In the bottom panel, we report various measures of fit for the models, providing validation that the specifications estimated do have explanatory power. In the last column of Table 3, assuming

[9] In logit regressions, all standard errors reported are robust and clustered by group.

the variables are primarily capturing the effects hypothesised, we summarize which of theoretical predictions the estimated coefficients best support.

For example, we claim that the estimated coefficient on the joint liability variable is most consistent with the BBG analysis rather than the effects predicted by the Stiglitz or Ghatak models. The positive and significant coefficient on ***'joint liability'*** supports the BBG as it indicates that groups whose members have an equal share have a 13.7% of higher probability of better loan performance compared to groups with unequally distributed loans. According to BBG, greater liability encourages members to apply group pressure to each other, increasing the repayment rate. In contrast AT found that as the degree of joint liability increases, repayment performance worsens. This was explained drawing on the moral hazard model of Stiglitz which emphasizes that borrowers would be more likely to take on risky projects as their repayment burden increased, and on the adverse selection model of Ghatak which predicts that a high degree of joint liability results in the expulsion of safe borrowers from the pool.

Our results on ***covariability*** (*SECTOR_DENSITYX* and *MANUFACTURING_PROP*) are consistent with the BC model. We find that the expected probability of paying on time decreases by 7.1% for groups with all members in the same sector. Also, as the ratio of members in a group in manufacturing increases, the expected probability of paying on time decreases by 10.6%. Increased correlation of returns means it is more likely that the borrower generates low returns when another borrower does so and so repayment performance is lower. This effect clearly outweighs any benefits that concentration might bring in terms of ability of screening and monitoring fellow group members. This result is consistent with previous findings. Zeller (1998) showed repayment rates increase with the level of diversification in the group's joint asset portfolio, while Paxton et al. (2000) found groups in rural areas to have more repayment problems compared to urban borrowers which they attributed to the higher degree of *covariate* risk associated with rural agricultural activities. Sadoulet and Carpenter

(2001) also found that diversity in groups helped to improve the repayment rates of the borrowers.

In contrast, the results provided on the symmetric (*SYMMETRIC*) returns broadly support Stiglitz's theory (i.e., safe project payoffs increase as the covariation of income of the borrowers' increases) and Ghatak's assertion that higher covariance attracts safer borrowers to the pool, resulting in higher repayment performance. Our results show that the expected probability of paying on time increases by 12.3% for the groups with symmetric projects returns of the group members. As Table A6 in the appendix shows average returns increased year-on-year for the sectors selected for the years the data providing a set of positive shocks for these groups. This result is consistent with Ahlin and Townsend (2007) which showed the negative effect of a series of bad years across villagers.

The result of **"*cooperation*"** (proxied by group names) was consistent with Stiglitz's model, with a positive significant effect on repayment.[10] Ceteris paribus, choice of such featured names results in decrease in default probability by 9.9% compared to groups without such featured names. Literature presents mixed evidence for cooperation. Several studies draw attention to the possibility that cooperation among borrowers can promote collusion against the lender. Al-Azzam and Mimouni (2012) show that the communication levels of group members are positively associated with on-time repayment, but higher levels of cooperation reduce repayment performance. Ahlin and Townsend (2007) find that cooperation among non-

[10] One concern regarding the group names was endogeneity. Group names was a variable we used as a proxy to measure social capital in a group. In order to see whether group names were determined endogenously, we ran 3 regressions with *GROUPNAME* as the dependent variable and different sets of variables as independent variable. The results presented in Table A8 in the Appendix show that the predictors are not significant in determining borrower's choice of names with those particular features, thus we have not found evidence for endogeneity. The predictors such as *TINT* and *NEWMEM* were found significant but these were irrelevant in picking the group name. On the other hand, the results show that as the average education of the group increases, the groups are more likely to pick such featured group names.

relatives is negatively related to repayment performance, while cooperation among relatives positively contributes to repayment performance.

The included explanatory variables which capture the ***'cost of monitoring'*** broadly support the BBG model, showing that increase in minimum walking distance between members is negatively associated with groups' performance; quantitatively, an increase of 15-minute walking distance across members results in a 1.1% increase in default probability. Longer distances across borrowers weaken the borrower's monitoring and enforcement ability (consistent with Wydick 1999; Karlan 2007; Cassar et al 2007 and Al-Azzam and Mimouni 2012). The evidence here is not completely consistent with the idea of strict relationship between distance and monitoring costs. Specifications which included the maximum distance between group members and a specification with the average distance (Table A5 specification 13) generally do not find any significant relationship between these variables and overall repayment probability (although in some specifications there is weak evidence of a positive relationship with maximum distance at 10% significance).

The results of the variables used to capture ***'screening'*** do not provide much evidence to support Ghatak's theory. A member's knowledge regarding each other's work (know type) as proxied by the variable same occupation was found to be positive and significant at 5% in two specifications. We do find that as the ratio of new members (*NEWMEMX*) in a group increases, the groups perform 17.5% better, although this coefficient is significant at only 10% in the mixed logit specification. This is consistent with Ahlin and Townsend (2007) which also found only weak evidence to support the Ghatak's theoretical predictions.

The estimated effects of the variables linked to ***'official and unofficial penalties'*** are consistent with the implications of the BC model and consistent with a range of previous studies (Wenner 1995; Wydick 1999; Paxton et al. 2000; Ahlin and Townsend 2007). The identity of the individual loan officers is significant, with groups who are under the supervision of Officer-F performing significantly 22.3% worse than those of under other officers (statistically significant at 1% level). This suggest that the way in which officers apply sanctions to the groups is important. It is also consistent with previous studies which show the effect of the loan officer and their characteristics on repayment performance (Van Den Berg et al. 2015; Agarwal and Wang 2008, Andersson 2004; Beck et al 2013, Kritikos and Vigenina 2005)

Both the existence of senior member and income differences within groups increase repayment performance (8.1%), and where these capture likely stronger leadership and hierarchical structure within the groups this is also suggestive of evidence consistent the BC model. The other measures reflecting age and educational differences in the groups are not statistically significant.

The main variable included to capture productivity effects, average education level within the group, is found to be significant and positive across all specifications, consistent with the previous evidence empirical findings (Zeller 1998; Matin 1997; Bhatt and Tang 2002). Bhatt and Tang (2002) argue that higher education levels contribute to understand complex information and take more profitable business decisions, more easily. Also, more educated borrowers have a better chance of finding part-time jobs creating extra sources of income. The other variable included to capture productivity is the average number of dependents of the group members. This is found to be positive but weakly significant and this does disappear in the specification without the squared term. Such an effect would be consistent with the view that borrowers with more dependents want to avoid jeopardizing the opportunity to access future credit (Sharma and Zeller 1997).

The final set of variables reported in Table 3 are those capturing the contract terms, including interest rate and loan amount. The results on interest rate conflict with all the theoretical predictions showing that higher interest rates are associated with better repayment performance. Abbink et al. 2006 provide one possible rationale for these results. In a laboratory experiment, they studied the behavioural impact of interest rates on the repayment of the groups and found two counteracting effects, one being the disciplining effect of high interest rates on borrowers (in terms of punishing voluntary defaults and free-riding), and the other being the more standard negative effect. Our results are suggestive of evidence which support the claim that higher interest rates can have a disciplining effect on borrowers which outweighs the negative impact standardly predicted.

The results on the impact of ***loan size*** were found to be significant and non-linear with both the loan size and its square found to be significant (being negative and positive respectively). These results mean the overall marginal effects of increasing loan size depends on the value at which this is calculated. It is negative at the mean loan value and for all values below this and is positive for all specifications at 15 percent above the mean loan value (Appendix Table A7). At lower loans values therefore, the results are consistent with Stiglitz and BBG's prediction as both models predict that repayment performance will decrease as borrowers undertake riskier projects. According to the BBG model, as the loan amount increases, the borrowers will be more likely to undertake risky projects to pay interest costs. This result is consistent with previous studies which suggest that as loan size increases repayment performance declines (Sharma and Zeller 1997; Godquin 2004; Mokhtar et al 2012).

As the loan amount become larger the BBG model predicts the lender's incentives to monitor the borrower increase. The result obtained here with the switch in the marginal effect for larger loans is consistent with idea that increased monitoring for these loan amounts improves repayment performance (Jimenez and Saurina 2004). Alternatively, this may be consistent with the evidence of economies of scale in returns so larger loans are more able to generate cash flow and profit therefore reducing repayment default (Roslan and Karim 2009;

Papias and Ganesan 2009; Nawai and Shariff 2012). We also found that the expected probability of on-time payment increases by 30.4% with a marginal change in the loan amount – income ratio.

Our results show the factors important for a successful repayment performance in a microcredit program in a metropolitan area comparing it with previous literature finding mostly from rural programs. The comparison of our findings and previous literature allows us to note how the repayment performance changes depending on differences regarding peer group behaviour and characteristics as well as the region's unique socioeconomic and cultural environment. The results are important for the policy implications as they shed light on how the programs' organisational structure, together with the type of loan officer may be effective for delivering appropriate services to a community.

6. Conclusion

This research provided new empirical evidence on determinants of repayment performance of joint-liability microcredits using a rich administrative dataset from an industrialized urban metropolitan setting. We empirically use predictions of four seminal theories on group lending by Stiglitz (1990); Banerjee, Besley and Guinnane (1994); Besley and Coate (1995); and Ghatak (1999); with the unified framework developed by Ahlin and Townsend (2007). We found that expected probability of paying on time increased by 9.9% for groups that chose names suggesting cooperation, solidarity and determination compared to groups without such featured names. Also, repayment performance deteriorated by 1.1% with a 15-min increase in the walking distance across group members. The results also show that; the groups with all members facilitating in the 'same' sector did not perform well probably due to the limited diversification of risk and this differed depending on the sector the borrowers were facilitating. We found that groups with members majorly engaged in manufacturing businesses perform significantly worse compared to groups with members majorly facilitating in trade and other sectors. The results also point to the importance of loan officers in affecting the repayment performance of the borrowers. Finally, existence of older members and new members in a group, higher degree of joint liability, having symmetric returns in “good years” of return, higher average education levels, higher level of interest rate, loan amount/income ratio and greater diversity in income improved the repayment performance. These empirical results highlight a range of possible considerations for MFIs in metropolitan settings to shape their policies to incentivize/enhance loan repayment, helping their self-sustainability and outreach.

While the existence of social capital and closer social relations may mean better screening and monitoring of joint liability group lending and may work better in rural areas, the results indicate that social capital plays an important role in metropolitan settings too. The strong positive relationship between group names and repayment, plus the importance of an age hierarchy within the groups provides evidence supporting this. Hence, these results suggest MFI investments in strengthening social capital of groups in metropolitan settings are worthwhile. For example, actions by the MFI which help the group clarify its objectives and strengthen its hierarchy are likely to increase repayment performance. Better understanding of how the exact role and development of social capital in metropolitan settings is a potential area for future research, e.g. how does the process of naming the group capture social capital, and what are the underlying mechanisms which lead to improved repayment performance?

There would seem to be several possible mechanisms at play. First, that the group names reflect the self-selection process and the initial social capital of the groups. In this case, the evidence provides another but a different measurement of social capital, though the implications are similar to previous studies where social capital has been found to be important. The second possible mechanism at work is that, process of group formation leads some groups to develop a clearer vision, identity and common purpose. In this case understanding why some groups create a better common purpose than others and how it might be influenced would be useful for policy and practice. Related to this, type of social capital may also be self-reinforcing with groups with more of this social capital potentially more able to develop common identity, and further understanding here could provide further insights useful for practitioners. In particular, it suggests that groups should be allowed to name themselves, and this will be superior to processes where groups are assigned names (or more likely group id codes, groups id numbers) by the MFI. Further, drawing on the wider social science evidence, that encouraging the use of a naming process could help create psychological ownership within groups leading to improved repayment outcomes. A final possible mechanism is that, certain group traits (related to group names) e.g. commitment, which are only observable by the MFIs are being used as a signal of likelihood of success and impact on how the group is treated. While these signals may provide good information on success probability, there is the potential for inequalities and inefficiencies to arise as a result which should be further considered.

Turning to the other implications from the study, the results also show the importance of loans officers in avoiding default suggesting MFIs could improve their performance by strengthening loan officer training. Identifying the key characteristics of successful loan officers is a potential area for further research. For example, in this context it is not clear whether differences in repayment performance associated with some loan officers arises from differences in their ability to enforce repayment, from better screening when picking customers, or more effective monitoring during the processes of repayment.

Metropolitan areas are competitive environments with a complex set of economic activities and businesses compared to rural settings. Although this may make it more difficult to develop profitable businesses at the individual level, the diversity of economic activities can be used as an option to enhance repayment performance. Our empirical results show that when the group members are concentrated in the same sector repayment performance deteriorates.

Interfering with the process of group formation may limit the strength of the groups in terms of their ability to screen and monitor. However, given that it is more possible in metropolitan settings, the results indicate that MFIs should be encouraging groups to form with a greater diversity of economic activities.

One of the limitations of the current research is that our data covers the periods after the banking crisis of Turkey (2000, 2011) and before the Global Financial crisis (2008) so we were not able to witness the impact of a negative macroeconomic shock on repayment performance. Research on the impact of diversity of economic activities on repayment performance during economic crisis times could provide further insights into whether joint liability schemes can exploit the greater economic diversity in metropolitan areas.

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Table 1 - Model Predictions

Variables	Model Predictions For Repayment Performance			
	Stiglitz (1990)	**Banerjee, Besley and Guinnane (1994)**	**Besley and Coate (1995)**	**Ghatak (1999)**
Joint liability	–	+	No Prediction	–
Positive correlation	+	No Prediction	–	+
Cooperative behaviour	+	–	–	No Prediction
Cost of monitoring	No Prediction	–	No Prediction	No Prediction
Official penalties	No Prediction	No Prediction	+	No Prediction
Unofficial penalties	No Prediction	No Prediction	+	No Prediction
Screening	No Prediction	No Prediction	No Prediction	+
Productivity	+	+	+	+
Interest rates	–	–	–	–
Loan size	–	–	No Prediction	+ / –

Note: The original models do not generate a prediction on the shaded-area variables. Shaded areas show the predictions of Ahlin and Townsend (2007) incorporated into the original models. + shows that repayment rate improves while – shows it deteriorates.

Table 2 - Descriptive Statistics

Variables	Description of the Variables	Mean	Standard Deviation	Quantiles					Skewness	Kurtosis
				Min	p25	Median	p75	Max		
Dependent Variable										
GNO_PENALTY	Dummy=1 if the group has never paid penalty during its current loan cycle, =0 otherwise	0.2035	0.4033	0	0	0	0	1	1.4729	3.1693
Joint Liability										
JOINT_LIABILITY	Dummy=1 if loan share is allocated equally across individual members of group.	0.5368	0.4995	0	0	1	1	1	-0.1478	1.0218
Covariance										
SECTOR_DENSITYX	Dummy=1 if all borrowers in the same group are in the same sector	0.4877	0.5007	0	0	0	1	1	0.0491	1.0024
MANUFACTURING_PROP	Ratio of members of the group doing business in manufacturing sector	0.3212	0.3495	0	0	0.33	0.67	1	0.6795	2.1607
TRADE_PROP	Ratio of members of the group doing business in trade sector	0.6019	0.3710	0	0.33	0.67	1	1	-0.3438	1.7200
OTHER_PROP	Ratio of members of the group doing business in other sectors	0.0769	0.1810	0	0	0	0	1	2.5496	9.5006
SYMMETRIC	Dummy=1 if all members have chosen proects which are more likely to succeed or default together	0.6351	0.4823	0	0	1	1	1	-0.5612	1.3150
Cooperation										
GROUPNAME	Dummy=1 if the group name consists of elements of solidarity, cooperation and togetherness	0.1684	0.3749	0	0	0	0	1	1.7720	4.1400
Cost of Monitoring										
MIN_DISTANCE	Length of time (in minutes) of walking distance between the two group members who live the closest to each other	23.4842	47.0774	1	1	5	18	300	3.3208	14.7817
MAX_DISTANCE	Length of time (in minutes) of walking distance between the two group members who live furthest from each other	106.5860	137.5781	1	16	47	145	1,000	2.3664	11.0498
AVE_DISTANCE	Average of minimum and maximum distance across group members	65.0351	85.0600	1	10	32.5	85	650	2.5271	12.4070
WORKING_OUTSIDE	Dummy=1 if the majority of the group members work outside	0.3684	0.4832	0	0	0	1	1	0.5455	1.2976
GROUPSIZE	Number of borrowers in the group	3.2596	0.5957	3	3	3	3	7	2.6446	11.0353
Screening										
OCCUPATION	Ratio of the borrowers doing the same type of business in a group	0.5713	0.2514	0	0.33	0.67	0.67	1	0.4120	1.9882
DRELATIVE	Dummy=1 if the group has at least two members with the same surname	0.2105	0.4084	0	0	0	0	1	1.4201	3.0167
NEWMEM	Dummy=1 if the group has at least one new member	0.0807	0.2729	0	0	0	0	1	3.0788	10.4791
NEWMEMX	Ratio of the new members in the group	0.0942	0.2108	0	0	0	0	1	2.3955	8.2954
Official and Unofficial Penalties										
OFFICER_F	Dummy=1 if the group is under the supervision of Officer-F	0.4281	0.4957	0	0	0	1	1	0.2907	1.0845
OFFICER_Y	Dummy=1 if the group is under the supervision of Officer-Y	0.5228	0.5004	0	0	1	1	1	-0.0913	1.0083
OFFICER_OTHER	Dummy=1 if the group is under the supervision of other officers	0.0491	0.2165	0	0	0	0	1	4.1724	18.4088
AGE_SANCTION	Dummy=1 if the group has a senior member (at least 25 years gap between youngest and oldest)	0.2246	0.4180	0	0	0	0	1	1.3201	2.7427
AGE_DIFF	Standard deviation of the age (years) of the borrowers in the group	7.9179	4.3937	0.49	4.07	7.88	10.59	26.07	0.8560	4.6410
INCOME_DIFF	Standard deviation of income of borrowers in the group	242.15	242.76	0	55.23	120.39	466.14	803.10	0.9042	2.2251
EDU_DIFF	Standard deviation of the education level of borrowers in the group	2.2856	1.2698	0	1.44	2.50	2.89	6.22	-0.2216	2.7785
Productivity										
AVE_EDU	Average education level of the borrowers (years)	8.2419	2.7263	0	6.78	8.26	10.24	15	-0.2903	2.7258
DEPENDENT	Average number of dependents of the borrowers in the same group	1.7641	0.8085	0	1.25	1.67	2.33	4	0.2529	3.0660
SQDEPENDENT	Square of the number of dependents of the borrowers in the same group	3.7635	3.1557	0	1.56	2.78	5.44	16	1.5174	5.9079
Contract Terms										
LAMOUNT	Loan size (amount) of the whole group	2848.96	910.83	400	2350	2700	3200	6,600	0.9331	5.2719
SQLAMOUNT	Square of the loan size of the whole group	8,943,284	6,155,106	160,000	5,522,500	7,290,000	10,200,000	43,600,000	2.3697	11.2409
TINT	Interest rate charged for the loan	56.6820	1.4366	49.14	56.69	56.70	56.70	62.82	-1.4359	22.5033
LAMOUNT_INCOME	Ratio of income to loan in a group	0.2013	0.1313	0.03	0.11	0.16	0.26	0.80	1.5980	5.6635
Control Variables										
GROUP AGE	Number of days the group exists at the day of the approval of the loan	88.6175	172.4872	0	0	0	153	871	2.0973	7.0676
MIN_LOANCYCLE	Minimum number of loans taken by the borrowers in the group at the approval day of the loan	1.1930	0.4456	1	1	1	1	3	2.2451	7.3989
MAX_LOANCYCLE	Maximum number of loans taken by the borrowers in the group at the approval day of the loan	1.4702	0.7714	1	1	1	2	5	1.6906	5.5100
4.LOANTERM	Loan term = 4 months	0.0456	0.2090	0	0	0	0	1	4.3556	19.9709
6.LOANTERM	Loan term = 6 months	0.0702	0.2559	0	0	0	0	1	3.3653	12.3255
8.LOANTERM	Loan term = 8 months	0.3860	0.4877	0	0	0	1	1	0.4685	1.2195
10.LOANTERM	Loan term = 10 months	0.2070	0.4059	0	0	0	0	1	1.4462	3.0916
12.LOANTERM	Loan term = 12 months	0.2912	0.4551	0	0	0	1	1	0.9190	1.8446

Table 3 - Regression Results (Other Results are in Appendix Table A5)

							PREFERRED REGRESSION -1			
		1st submitted version (but Officer F used) Spec (1) clus(clus)	1st submitted version (but Officer F used) Spec (3) clus(clus)	For 2nd submission omitted insig. Vars.	Same as peferred regression but we have Officer Y and Officer Other	Same as preferred Regression but omitted high correlated vars , MAX_DIST + SQMEANDEP	Preferred Regression-1	PR1 margins at means	PR1 Odds Ratio	PR1 xtmelogit	Supporting Theory
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	
Joint Liability	***Joint Liability***										
JOINT_LIABILITY	eskiJOINT_LIABILITY	1.718***	1.672***	1.600***	1.808***	1.627***	1.796***	0.137***	6.028***	2.053***	BBG
		(0.529)	(0.464)	(0.429)	(0.526)	(0.492)	(0.522)	(0.0356)	(3.1494)	(0.765)	
Covariance	***Covariance***										
SECTOR_DENSITYX	eskiSECTOR_DENSITYX	-1.105*	-0.930*	-1.003*	-0.936**	-0.741*	-0.931**	-0.071**	0.394**	-1.080*	BC
		(0.655)	(0.551)	(0.569)	(0.443)	(0.413)	(0.445)	(0.0321)	(0.1754)	(0.582)	
TRADE_PROP	eskiTRADE_PROP	0.920									
		(0.624)									
OTHER_PROP	eskiOTHER_PROP	1.607									Stiglitz and Ghatak
		(1.217)									
MANUFACTURING_PROP	eskiMANUFACTURING_PROP				-1.368**	-1.380**	-1.387**	-0.106**	0.250**	-1.483*	BC
					(0.685)	(0.664)	(0.661)	(0.0489)	(0.1653)	(0.774)	
SYMMETRIC	eskisymm	1.566***			1.617***	1.463***	1.612***	0.123***	5.013***	1.893***	Stiglitz and Ghatak
		(0.590)			(0.460)	(0.442)	(0.463)	(0.0347)	(2.3220)	(0.731)	
Cooperation	***Cooperation***										
GROUPNAME	eskiGROUPNAME_HETERO	1.123**	0.874*	0.777*	1.288***	1.177**	1.296***	0.099***	3.656***	1.516**	Stiglitz
		(0.536)	(0.480)	(0.465)	(0.463)	(0.463)	(0.462)	(0.0346)	(1.6876)	(0.723)	
Cost of Monitoring	***Cost of Monitoring***										
MIN_DISTANCE	eskiMIN_DISTANCE	-0.0111**	-0.00697*	-0.0116**	-0.00917**	-0.00610*	-0.00914**	-0.0007**	0.991**	-0.00977	
		(0.00514)	(0.00382)	(0.00498)	(0.00439)	(0.00364)	(0.00439)	(0.0004)	(0.0044)	(0.00601)	
MAX_DISTANCE	eskiMAX_DISTANCE	0.00267		0.00255	0.00286		0.00285	0.0002*	1.003	0.00291	
		(0.00193)		(0.00160)	(0.00184)		(0.0019)	(0.0001)	(0.0019)	(0.00220)	
WORKING_OUTSIDE	eskiWORKING_OUTSIDE	0.608									BBG
		(0.521)									
GROUPSIZE	eskiGROUPSIZE	-0.150	-0.104								
		(0.589)	(0.488)								
Screening	***Screening***										
OCCUPATION	eskiOCCUPATION	1.467	2.298**	2.467**							
		(1.174)	(1.099)	(1.063)							
NEWMEM	eskinewmemingroup	-1.186									
		(0.759)									
NEWMEMX	newmem1				2.292**	2.528**	2.294**	0.175*	9.911**	2.551*	Ghatak
					(1.116)	(1.082)	(1.116)	(0.0900)	(11.062)	(1.456)	
DRELATIVE	eskiDRELATIVE	0.383									
		(0.475)									
Official and Unofficial Penalties	***Official and Unofficial Penalties***										
OFFICER_Y	eskiOFFICER_Y				2.908***						
					(0.500)						
OFFICER_OTHER	eskiOFFICER_OTHER				3.035***						
					(0.788)						
OFFICER_F	eskiOFFICER_F	-2.881***	-2.534***	-2.390***		-2.865***	-2.916***	-0.223***	0.054***	-3.420***	
		(0.531)	(0.494)	(0.470)		(0.471)	(0.489)	(0.0450)	(0.0265)	(1.025)	
AGE_SANCTION	eskiAGE_SANCTION	1.734**	0.962**		1.069**	1.033**	1.066**	0.081**	2.903**	1.226*	BC
		(0.741)	(0.446)		(0.468)	(0.476)	(0.471)	(0.0384)	(1.3667)	(0.661)	
INCOME_DIFF	eskiINCOME_DIFF	0.00195**	0.00190**	0.00182**							
		(0.000934)	(0.000758)	(0.000782)							
EDU_DIFF	eskiEDU_DIFF	-0.0882									
		(0.184)									
AGE_DIFF	eskiAGE_DIFF	-0.108									
		(0.0798)									
Productivity	***Productivity***										
AVEEDU	eskiAVEEDU	0.226**	0.233***	0.172**	0.259***	0.268***	0.260***	0.020**	1.297***	0.302**	
		(0.105)	(0.0815)	(0.0778)	(0.0982)	(0.0943)	(0.0979)	(0.0090)	(0.1270)	(0.126)	
MEANDEPEND	eskiMEANDEPEND	1.608*			1.397*	0.247	1.400*	0.107*	4.055*	1.836	All models
		(0.842)			(0.794)	(0.277)	(0.793)	(0.0640)	(3.2143)	(1.231)	
SQMEANDEP	eskiSQMEANDEP	-0.363*			-0.294		-0.295	-0.023	0.745	-0.389	
		(0.202)			(0.207)		(0.206)	(0.0160)	(0.1537)	(0.285)	
Contract Terms	***Contract Terms***										
TINT	eskiTINT	0.441***	0.270**	0.194	0.394**	0.367**	0.398**	0.030**	1.490**	0.467**	None of the models
		(0.141)	(0.132)	(0.132)	(0.161)	(0.162)	(0.157)	(0.0118)	(0.2333)	(0.227)	
LAMOUNT	eskiLAMOUNT	-0.00234**	-0.00222**	-0.00173**	-0.00201**	-0.00192**	-0.00205**	-0.0002**	0.998**	-0.00212*	
		(0.000927)	(0.000993)	(0.000749)	(0.000909)	(0.000880)	-0.0009	(0.0001)	(0.0009)	(0.00114)	Stiglitz and BBG
SQLAMOUNT	eskiSQLAMOUNT	3.96e-07**	3.81e-07**	2.95e-07***	3.44e-07***	3.25e-07**	3.48e-07***	2.66e-08***	1.000***	3.58e-07**	
		(1.54e-07)	(1.61e-07)	(1.06e-07)	(1.33e-07)	(1.28e-07)	(1.30e-07)	(0.0000)	(1.30e-07)	(1.73e-07)	
LAMOUNT_INCOME	lamount_income				3.985**	3.598**	3.982**	0.304**	53.633**	4.887**	
					(1.676)	(1.709)	(1.675)	(0.1407)	(89.8484)	(2.378)	
Control Variables	***Control Variables***										
GROUPAGE		Yes	Yes	No	No	No	No	No	No	No	
LOAN CYCLE		Yes	Yes	Yes	No	No	No	No	No	No	
LOAN TERM		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Constant	Constant	-29.40***	-18.06**	-13.30*	-30.08***	-24.38**	-27.29***		1.40e-12***	-32.44**	
		(9.316)	(8.521)	(7.978)	(9.746)	(9.728)	(9.531)		(1.34e-11)	(14.64)	
Observations	Observations	285	285	285	285	285	285	285	285	285	
Pseudo R2	Pseudo R2	0.399	0.334	0.308	0.379	0.365	0.379		0.379		
Number of groups	Number of groups									211	
AIC		0.839	0.827	0.832	0.796	0.789	0.789	0.782	0.789		
BIC		-1251.211	-1294.812	-1304.372	-1296.389	-1309.333	-1302.024	-1302.024	-1302.024		
ROC		0.8967	0.8743	0.863	0.886	0.8801	0.8861	0.8861	0.8861		
LL		-86.608	-95.896	-99.595	-89.455	-91.462	-89.464	-89.464	-89.464		

Robust standard errors clustered by group in parentheses
*** p<0.01, ** p<0.05, * p<0.1