Does the Microfinance Lending Model Actually Work?

by Rafael Gómez and Eric Santor

Microfinance institutions (MFIs) have expanded throughout the developing and developed world and now serve over 10 million households worldwide.[1] Despite the relative poverty of their clients, MFIs have been able to extend credit to poor households, while still maintaining high repayment rates and financial sustainability. Much of this success has been attributed to MFIs innovative use of peer group lending—the practice of allocating loans to individuals with little or no collateral—but with social capital in the form of peers who are also co-applicants and who in many cases are jointly liable. Practitioners and pundits attest to the ability of group lending to increase incomes, consumption, and the stock of human capital for those households facing severe credit constraints. Recent theoretical and empirical work, however, has begun to cast doubts on many of these claims.[2] Not surprisingly, the apparent success, or lack thereof, of peer group lending has drawn the attention of numerous development researchers.

This paper wades into the microfinance debate by tackling two important problems. First, by directly comparing the repayment outcomes of group members to those of traditional individual borrowers, we go further than most previous studies that have only examined the relative performance of peer groups with different characteristics. Second, the paper addresses the question of *how* group lending operates by measuring the effects that peer group lending has on borrower incentives and the shaping of selection into the peer group program. In other words, the paper deals squarely with two questions that still remain largely unanswered in the microfinance literature: Does peer group lending lead to higher repayment rates when compared to traditional individual lending techniques? And if so, does the beneficial peer group effect stem from greater *ex post* borrower effort or positive *ex ante* selection into the group lending program? These questions lie at the heart of current microfinance debates and therefore warrant close empirical scrutiny. Answering the first question would—depending on the answer—legitimize or perhaps call into question MFIs preference for using group lending schemes over traditional individual liability. Conversely, a positive response to the second question

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would confirm practitioner claims that group lending programs not only perform a useful sorting function, but also provide positive effects to those enrolled by inducing higher levels of repayment effort.

There are a number of difficulties in comparing individual lending methods and group lending methods, such as the relative rarity of the same MFI providing both types of loans in the same geographic area, with rich enough data to distinguish among potential channels of peer group influence. Because we have access to such an MFI, we were able to find evidence to support the claim that those enrolled in peer group lending programs are less likely to default as compared to individual borrowers. By comparing the estimates obtained through a standard probability equation to those found using propensity score matching methods, we find that the peer group effect works almost equally through the dual channels of selection into the group lending program and greater borrower effort once inside.[3]

The paper is organized as follows: Section I outlines the central theoretical and empirical claims and reviews the relevant literature. Section II describes how the data was collected and presents descriptive statistics. Section III describes the empirical methodology used. Section IV presents the empirical results and Section V offers conclusions and areas of further research.

Why Should Peer Group Members Outperform Individual Borrowers?

Previous Theoretical Literature

Considerable theoretical attention has been paid to understanding how group lending works and what affect it may have in practice. Most theoretical studies have focused on how peer group schemes can overcome the inherent problems associated with credit constraints and asymmetric information in financial markets.[4] Specifically, in a world where borrowers lack collateral, group lending has been shown to mitigate problems associated with adverse selection, moral hazard, contract enforcement, and state verification.[5] Group lending with joint liability overcomes these problems by passing the monitoring activity onto the borrowers themselves. The underlying idea is that group members will monitor their peers and pressure individuals who might misuse their loans not to do so.[6] While this monitoring activity is costly for the borrower, it is assumed to be much less costly than for the lender, since group members will typically know each other well in advance of the date of borrowing. Ghatak and Guinanne (1999) show that when compared to an individual liability contract, entrepreneurial effort will be strictly higher under peer group lending with joint liability, assuming, of course, that monitoring costs are low and social sanctions are effective.[7] For the purposes of this paper, effort is defined as actions that would contribute to the success of entrepreneurial activity, and hence to greater repayment probabilities.

Recent theoretical work, however, has begun to cast a skeptical eye on peer group lending, suggesting that a range of simpler borrowing schemes (from greater lender monitoring to regular repayment schedules) offer more effective repayment techniques than peer group liability.[8] Other researchers, even those with favorable views towards peer group lending, acknowledge that peer group pressure may generate conflicts, which may negate the positive benefits associated with group liability.[9]

Theoretical models seem to demonstrate that peer group schemes tend to induce higher levels of repayment effort due to intra-group monitoring and greater peer pressure. However, whether peer group schemes outperform traditional individual liability is still an open question in the theoretical literature.

Previous Empirical Literature

Despite the competing predictions of a number of group lending models, some scholars indicate that there is little or no direct empirical evidence to suggest that peer group borrowers actually outperform individual borrowers.[10] While it is true that closer monitoring and increased effort is inherently difficult to measure, the consequences of these positive peer group effects should be easier to observe; group members should outperform individual borrowers in terms of repayment success, if other factors remain constant.[11] Most empirical studies, however, have examined the relative performance of groups with different characteristics, as opposed to testing whether peer group lending improves upon traditional individual liability schemes. Moreover, by focusing only on group borrowers, empirical research has been unable to distinguish among potential channels of peer group influence (i.e., endogenous program participation or greater borrower side effort).

For instance, Ahlin and Townsend (2003) test a wide range of the predictions of group lending with joint liability, such as the impact of interest rates, loan size, the degree of joint liability, group homogeneity, and the level of group monitoring and social sanctions on repayment rates. Although much of their evidence confirms the predictions of theory, they also find evidence that contradicts some of the predictions of group lending, such as strong social ties, group monitoring, and group cooperation, which are negatively related to repayment.[12] The authors suggest that the widely held notion that groups succeed because of their ability to access and make use of social capital is more nuanced in practice, based on the fact that in some situations strong social cohesion within groups may lead to weak incentives to repay (i.e., in larger urban environments where joint default would not lead to a social stigma). In the end, they conclude that the idea that social ties are positive for group lending must be qualified, given that social structures that enable penalties can be helpful for repayment, while those which discourage them can lower repayment. Karlan (2003), in this vein, shows that higher levels of social capital in groups is positively correlated with repayment, particularly when enabled by the appropriate environment.[13] Work by Wydick (1999) suggests greater levels of social cohesion, like knowing group members prior to group formation or living in the same neighborhood as other borrowers, can lead to lower levels of individual default.[14] Wenner (1995) offers similar evidence that socially cohesive groups have higher repayment rates.[15] Specifically, his work indicates that repayment performance of groups improves when groups have formally stated rules prescribing how members should behave. This variable captures the many screening, monitoring and enforcement activities that take place within the groups. Another variable that is found to positively affect repayment is the location of groups (e.g., if groups are located in remote areas this reduces their possibilities for access to alternative sources of credit, which stimulates them to ensure group repayment as much as possible in order to have future access to loans).

In summary, published empirical studies—while confirming many of the key predictions of group lending—have yet to address two principal theoretical conjectures: does group lending lead to lower default rates when compared to conventional individual lending and does this effect exist due to positive selection into the peer group program and/or the result of greater borrower effort once inside the group?

In order to answer the two questions above, we analyze the performance of microfinance borrowers from two North American microfinance organizations: Toronto based Calmeadow Metrofund and Halifax based Calmeadow Nova Scotia. We begin by describing the group and individual lending mechanisms used by these organizations and then follow up with a description of the data and summary statistics.

Microfinance Program Lending Characteristics and Data

Calmeadow's Lending Mechanism

Calmeadow Metrofund and Calmeadow Nova Scotia offer two types of loans, group and individual. Group loans could range in size from \$500 to \$5000 with \$1000 being the typical loan size for first time borrowers. The loan term is typically twelve months and early repayment is an option with no penalty.[16] The group lending format has the following features. Any group of four to seven borrowers may apply for a loan from Calmeadow, and borrowers must form their group before applying for a loan.[17] For the loan application, group borrowers must provide personal information, references, as well as business and demographic information. The information on this form must then be checked and approved by all other group members. Group members are encouraged to rigorously assess the credit worthiness and entrepreneurial competence of their potential peer-group members. Submission of the group's loan applications occur once group members have approved each other's applications. Calmeadow loan managers then assess the group's application using a series of credit checks. Upon Calmeadow's approval, group members receive their loans all at the same time. Group members, though not strictly liable for each other's loans, are ineligible to access subsequent loans if one group member falls into arrears and is not currently "paid up." In this way, joint liability is implemented.[18]

Calmeadow also offers individual loans that could range in size from \$1000 to \$15000 over longer terms (up to 60 months), for which anyone can apply.[19] Group borrowers who successfully repay a sequence of group loans may eventually graduate to an individual loan, although this does not occur often in practice: most individual borrowers did not come from previously successful groups. The screening process is more rigorous than group loans; borrowers must be registered, have an existing business over twelve months old, provide a more sophisticated business plan, and occasionally provide collateral (usually the fixed asset purchased with loan funds).[20] Consequently, Calmeadow views individual borrowers as being "better" clients in terms of loan application requirements. The borrowers' criteria for both individual and group loans is explicitly stated in Calmeadow's promotional literature and repeated during information sessions before potential borrowers decide whether to apply for an individual or group loan.

The consequences of non-repayment are substantial for both group and individual borrowers. For group borrowers, failure to repay means that their fellow group members will not be able to access future loans from Calmeadow and consequently can expect to incur the cost of social sanctions imposed by their fellow peer group members. For both group and individual borrowers there are substantial individual costs to non-repayment, that are independent of the joint liability costs, because defaulting on a loan results in the serious deterioration of that individual's credit history and in the submission of the loan claim to a collection agency. This will result in the individual's inability to access any formal credit in the future.

Data

There are 995 group and 394 individual borrowers who accessed loans from Calmeadow Metrofund and Calmeadow Nova Scotia, which represent the entire population of Calmeadow clients from January 1, 1994 to August 30, 1999.[21] Of these borrowers, 136 had not completed their loan repayment cycle by August 30, 2000 and have been removed from the sample. For the remaining borrowers, we collect repayment history from the electronic loan-tracking system, and demographic, business, and household data from the loan application contained in their client file.[22] The data was further supplemented by a telephone survey for all current and past borrowers which was conducted by the authors that measured borrower attitudes towards repayment and other normally hard-to-observe characteristics such as the nature and abundance of social ties.[23] There are 1064 borrowers who contain at least some or all of this data. For the regression analysis, the sample size is reduced from this potential total, as we limit the sample only to those borrowers who have data for all the relevant characteristics.

Comparative Loan Term Statistics

In this section, we provide descriptive statistics of Calmeadow's clients, with particular emphasis placed on the differences between group and individual borrowers, and successful and delinquent borrowers. Beginning with the former, the data reveals that roughly 21.2 percent of all group borrowers and 41.4 percent of all individual borrowers have defaulted on their loans (see Table 1).[24] Likewise, 38.4

percent of group borrowers and 88.7 percent of individual borrowers have an "NSF", which implies a missed payment, recorded on their loan. In terms of the ratio of write-offs-to-outstanding loan portfolio, the arrears rate is approximately 8 percent.[25]

The actual size of group and individual loans fell within the lending guidelines set out by Calmeadow. Group loans ranged from $500 to $5000 and individual loans ranged from $1000 to $15000, with mean and median loan sizes of $1031 and $1000 for group loans and $3954 and $2700 for individual loans respectively. Loan terms varied from six to twenty-four months for group loans while individual loans offered longer terms to a maximum of sixty months. The cost of both types of loans was 12 percent plus a 6.5 percent up-front administrative fee. Loan payments averaged $95 per month for group borrowers and $220 per month for individual borrowers. Group loans were typically used for working capital, while individual loans were often used for working capital and/or the purchase of fixed assets such as computers and office equipment.

Group versus Individual Borrowers

There are several key demographic differences between group and individual borrowers. Group borrowers are more likely to be female than male (54 vs. 46 percent), Hispanic (9.3 vs. 3.3 percent), and immigrants (42 vs. 25 percent), while individual borrowers are more likely to be African, male, and Canadian born (See Table 1). Both group and individual borrowers have similar education and skills training related to their business activity. With respect to business and household characteristics, individual borrowers have higher monthly (non enterprise) incomes than group borrowers ($1,826 vs. $1,449) but less access to outside sources of credit (see row 1 in Table 2). Although there are still many startups in both group and individual borrower segments (37.5 vs. 33.6 percent respectively), individual borrowers have larger enterprises (by revenue), that are more likely to be located outside the home (33.6 vs. 24.1 percent) and earning higher monthly profits than group borrowers ($2,392 vs. $845). Interestingly, the ratio of household income to loan payment was higher for group than individual borrowers (16.9 vs. 12.5 percent), whereas the opposite was true for the ratio of business revenue to loan payment (26.1 vs. 32.9 percent).

Delinquent versus Successful Borrowers

There are significant differences between delinquent and successful (paid client) borrowers. In terms of loan terms and size, delinquent borrowers tend to have, at the mean, slightly larger loans with longer terms and larger monthly payments than successful borrowers (see Table 1 last two columns). Demographically, delinquent borrowers are more likely to be single, male, and born in Canada, with less education and significantly lower levels of business related skills training than successful borrowers. With delinquent borrowers, household income is slightly lower than successful borrowers, but statistically similar (row 6 in Table 2 last two columns).

While less than a majority of delinquent borrowers lack outside sources of credit as compared to successful paid clients (45 vs. 65 percent), the few that do have outside credit often overuse it and also are more likely to have poor credit history (results not shown). In terms of business type, there are only a few significant differences in terms of revenues, profits and ownership type between delinquent and paid clients. However, delinquent as opposed to successful paid businesses are more likely to be startups (44.0 vs. 34.7 percent) and located outside the home in a store/shop (30.5 vs. 23.9 percent). The ratio of household income to loan payment is higher for successful borrowers, but business revenues and profits to loan payment are higher for delinquent borrowers. Furthermore, within the groups themselves, attitudinal differences appear in the survey data. Those borrowers who knew more of their fellow members before forming the peer group at Calmeadow were less likely to default (42.0 vs. 57 percent). Delinquent borrowers were also less likely to feel a moral obligation to repay their loans. Likewise, default was less likely if a great deal of trust existed in the group or if group members felt a moral obligation to their peers. Lastly, those individuals with greater "social ties" were less likely to default than individuals who did not belong to an association, club, or sports team.[26]

Empirical Approach

The hypothesis that group borrowers should outperform individual borrowers in terms of loan repayment is first tested using a standard probit model for the entire sample of individual and group borrowers. If the presence of peer group lending shapes positive borrower selection and/or induces higher levels of entrepreneurial effort (and greater incentives to pay back the loan) , then a peer group dummy (identifying participation in a peer group program) should be negative and significant with respect to the probability of default. Because the standard *probit* estimate cannot distinguish among channels of peer group influence (i.e., *ex post* incentives or *ex ante* selection) we treat this as an *overall* measure of the peer group effect (i.e., it captures the combined effect of selection and incentive impacts).

In order to isolate the mechanisms by which group lending operates, we go on to correct for selection bias by applying a propensity score matching method. We then compare the results from the matching method approach to the original *probit* estimates. If the peer group effect remains large and significant after propensity score matching, we can infer that peer group incentives are an operative feature of the peer lending program. This is so because propensity matching can provide a much closer 'like with like' comparison of clients in and outside the group program, thus picking up the 'selection' effect of borrowers who are inherently more hard working and less likely to default before joining the group borrowing program. Although standard selection correction estimates (IV) could also be used to correct for this selection effect, we focus on propensity score matching methods as they do not assume that group lending program participation would affect participants and non-participants equally. Matching methods are still not as common in the microfinance literature and are therefore discussed in greater detail below.

How Do We Isolate the Channels of Peer Group Effectiveness?

A useful way of isolating the incentive channels in our probit equation is to consider the peer group dummy as the "treatment" effect of belonging to a peer group. If program participation is exogenous, then the decision to apply for and receive a group loan is independent of the probability of default and the peer group lending estimate will provide an unbiased measure of the treatment, or incentive, effect. In the case of Calmeadow's lending program, however, it is evident that participation is not exogenous, as only those borrowers that have large projects and sufficient collateral are able to access the individual loan program.[27] Consequently, it is necessary to determine how endogenous program participation will bias the results and how this bias can be accounted for in the estimation procedure.[28] In this regard, a treatment effects model can be estimated following Greene (2000).29 In this framework, one estimates the average impact of program participation as:

$$\theta = E(D_1 | G=1) - E(D_0 | G=0) \quad (1)$$

where θ is the peer group effect, E is the effort, D_1 is the outcome if the treatment is taken up, D_0 if not, G=1 indicates that the borrower was eligible to take up the treatment, G=0 otherwise.

Though useful, the non-experimental technique described above relies on the fact that the treatment and control groups share common supports for the distribution of borrower characteristics. There are several disadvantages to this approach; most importantly, if the supports of the distribution are not similar — i.e., borrowers in the treatment and control group are not comparable across a range of characteristics such as income, education, or gender— Heckman et al. (1996) show that the implementation of standard non-experimental techniques may produce biased estimates of program impacts.[30]

To more accurately assess the impact of the program, we calculate the effect of the treatment (the group lending program) on the treated (those who accessed the program):

$$\theta_T = E(D_1 | G=1) - E(D_0 | G=0) \quad (2)$$

That is, we observe the outcomes of the borrowers that received the treatment and compare them to a set of borrowers that are otherwise identical, except for the fact that the control group did not have access to the program, but are eligible to take up the treatment and would do so given its availability. Unfortunately, the second term of the right hand side of equation (2) $E(D_0 | G=1)$ does not exist in the data since it has not been served.[31]

However, there is a solution to this evaluation problem: to create the counterfactual $E(D_0 | G=1)$ by matching treatment and control borrowers along observable characteristics. For every borrower in the treatment, one can find an individual borrower that is identical in every observed respect, except for the availability of a group lending loan. Since there are many dimensions along which to match borrowers, finding comparable matches using conventional method is difficult. To solve this problem, we institute propensity score matching methods, which instead of matching along *X*, matches along *P(X)*, the probability that the borrower participated in the treatment group.[32] The advantage of matching is that it exploits all the endogenous information on program participation, without the need to identify program participation through functional form or excluded instruments.[33]

Results

Does Belonging to a Peer Group Reduce Borrower Default?

The results from estimating our initial probit model are presented in Table 3. The effect of being in a group, even when controlling for many variables typically associated with default, is negative in all specifications (see columns [1] through [4]). In Table 3 column [1], we find that the probit coefficients imply marginal effects such that group lending reduces the probability of default by 23 percent when compared to individual lending (the original probit coefficientsefficient are available in Appendix Table 3A). When one controls for demographic characteristics in column [2], such as whether the borrower is married, self-employment business training, an immigrant as well as their household income, the peer group effect remains quantitatively similar and significant. In column [3] we cluster the standard errors (around group) and add controls that capture loan size and business characteristics such as whether the business is home based, a start-up and profits. The peer group coefficient, though slightly lower, still remains significant.[34] The fact that the peer group dummy seems to matter even after clustering, and after one controls for the smaller loans and the differential business characteristics of group borrowers—factors that imply a lower degree of default risk—is indicative, perhaps, of the fact that peer group lending does more than just shape the selection process of borrowers and instead, provides positive incentive effects.[35]

Lastly, we explore whether the definition of default affects the results. Default can be defined more narrowly as only those loans that are written off. Thus, borrowers who had loans sent to collections or who missed multiple payments can be considered to have "successfully" repaid their loans. This reduces the number of default observations from 155 to 107, or from 22.0 to 14.9 percent of borrowers. In Table 3 column [4], the results using this narrower definition of default are shown to be qualitatively similar to those from specification [3]. While belonging to a peer group significantly lowers the probability of default, the coefficient is only 9 percent lower with the narrower definition of default.

One preliminary interpretation of these results is that the anticipated incentive effects associated with group lending (i.e., positive peer pressure and increased borrower effort) appear to be an operative feature of the group lending mechanism.

Accounting for Selection into the Peer Group Program

Propensity Score Matching Methods Estimates

We now test for the effect of selection into the program. A probit regression is first estimated and the marginal effect results are presented in Table 4 (the original probit coefficientsefficient are available in Appendix Table 4A).[36] For each borrower, a propensity score is generated from the predicted value of the probit index. The propensity score is then utilized to match those borrowers in the treatment group to their nearest (individual borrower) neighbor. When a match does not exist, the borrower is removed from the sample until all borrowers are matched with their nearest neighbor. A simple trimming procedure is conducted to account for the possibility that the distribution of propensity scores is skewed. Following Ham et al. (2003), propensity scores that fall below/above a certain level are removed from the sample until a total of 5 percent of the total sample is eliminated. The procedure is also conducted for trimming at the 10 percent and 15 percent levels respectively.

The results are presented in Table 5 for no trimming, and for 5 percent, 10 percent and 15 percent trimming levels.[37] For the simple matching without replacement, the results cohere with the standard probit results in Table 3, in that the peer group dummy coefficient reported in all four columns remain large and significant in all but one case (explained below), indicating that incentive effects are an operative feature of the group lending program. For the simple dummy variable approach used originally in Table 3 column [1], we find that the analogous results in Table 5 columns [1] and [2] confirm that belonging to a peer group tends to significantly reduce the likelihood of borrower default. It is important to note that if selection is the most important factor driving the peer group effect, then when we attempt to correct for selection using these matching estimates, the coefficient for the peer group dummy should fall and approach zero should no incentive effects be at work.

Estimation of the full specification, the specification with all our controls and found in column [3] of Table 3, leads to similar probit coefficients on our peer group dummy, although lack of precision in the non-replacement estimates leads to a statistically insignificant result in Table 5 column [3]. However, when replacements are used in Table 5 column [4] and the sample is trimmed to ensure common supports, the effect of peer group membership increases and once again becomes significant. This is owing to the fact that replacement with trimming removes those group borrowers whose propensity score is close to one—i.e., those borrowers who would not have been able to qualify for an individual loan or who preferred the peer group model. This group of excluded borrowers typically had poor credit risks, leading to a lower estimated peer group effect.

One interesting feature of all the matching methods estimates is that the peer group effect is nearly three times as large as the baseline probit estimates. Since those baseline estimates do not control for selection, one can infer that the incentive effects are quite strong and offset negative selection into the peer group program, since selection into peer group seems to imply a greater likelihood of default as compared to individual borrowers. In other words, the MFI screening program which streamlines applicants of higher quality and more business experience into individual loans and those of less business experience into group loans does seem to work. The peer group program seems to select the right individuals and improve their repayment rates once inside the peer group program.

Robustness Check: Comparing Probit Results Across Peer Loan Sub-Groups

When one considers the nature of the groups included in the sample, the use of matching methods in Table 5 still may not capture the *total* selection effect associated with peer group lending. For peer group lending to be effective, group members must believe that their fellow borrowers can and will enforce social sanctions on them. Naturally, this can only be true if the borrowers know and trust each other. If groups were made up of individuals who have little or no connection with each other, the peer group effect would be greatly weakened. The treatment and matching results may be picking up this feature; namely, the sample of group borrowers includes groups that do not know and trust each other well.

To account for this, groups are clustered by levels of self-reported trust and the estimation results presented across two specifications (rows 1 to 2) in Table 6. The results in column [1] show that when high trust groups are excluded, the peer group effect though significant, is not as strong. On the other hand, when only high trust groups are included, the estimate of the effect of peer group membership becomes larger than the original sample pool (see column [2]). This confirms that peer group lending is more effective when groups know and trust each other.

We also check to see if the effect of lower default within peer groups may be simply driven by their smaller loan sizes. To this end, we limit the sample in columns [3] and [4] to only group and individual borrowers with loans no greater than $1000 and $2000. The results still show that group lending leads to lower default rates.

Conclusion

Many theoretical models of group lending drawn from the microfinance literature predict that peer pressure and monitoring will lead to more effective borrower-side selection and greater borrower effort. While these effects are hard to measure, one should expect that if operative, group borrowers would outperform individual borrowers in terms of repayment success. Unlike previous empirical work in the microfinance literature that has examined differences among group borrowers only, we find evidence consistent with these theoretical claims; namely, group lending outperforms conventional individual lending techniques in terms of repayment success. We apportion this group lending effect, almost equally, to the twin effects of *ex ante* selection into the group lending program and greater *ex post* borrower effort once inside. However, since these channels have been estimated rather than measured, one must nevertheless be cautious about whether group lending works *as predicted* in theory and as touted by practitioners. It should also be acknowledged that the effectiveness of peer group lending is moderated by observed sources of variance such as the size of the loan, the quality of the loan manager, levels of trust within a group, and the enforcement of social norms within the group and in the surrounding neighborhood.

The evidence presented in this paper also raises several important future areas of research. First, while peer groups do appear to work for MFIs, how are group norms actually enforced? Is it the case that *all* borrowers exert greater effort in groups than on their own? If so, is this loan technique optimal in formal banking situations where borrowers do not face such severe credit constraints? Lastly, is there a link between the incidence of borrower default and the level of earnings? Exploring this potential mean-variance tradeoff could be insightful. It is clear that further empirical work is necessary to resolve these questions. Our hope is that this work has perhaps laid the foundations for future scholarly investigation in this area.

TABLE 1 - BORROWER SUMMARY STATISTICS[37]

	All Clients (n=1064)	Group Clients (n=902)	Individual Clients (n=162)	Delinquent Clients* (n=258)	Paid Clients* (N=806)
Loan Terms, Characteristics, and Delinquency Rates					
1. Loan Size ($)	1415	956	4008	1716	1319
	(1000)	(1000)	(2631)	(1000)	(1000)
2. Loan Term	12.8	10.9	23.2	14.4	12.3
(months)	(12.0)	(12.0)	(18.0)	(12.0)	(12.0)
3. Loan Payment	107.0	92.5	218.7	114.3	105.0
($/month)	(88.9)	(88.9)	(184.3)	(88.9)	(88.9)
4. Default (%)	24.3	21.2	41.4		
Demographic Characteristics					
5. Gender					
Male	46.6	46.1	49.4	56.6	43.4
6. Ethnicity					
Caucasian	50.8	51.0	49.4	50.6	50.8
Europe/Arabic	2.0	2.1	1.3	0.0	2.6
African	33.7	32.1	42.9	43.9	30.4
East/South Asian	4.0	4.1	3.3	2.4	4.5
Hispanics	8.4	9.3	3.3	2.8	10.2
Other	1.2	1.3	0.0	0.4	1.4
7. Immigrant Status					
Immigrant	39.8	42.4	25.0	33.5	41.9
8. Marital Status					
Single*	46.4	46.7	43.9	50.0	45.3
Married	53.6	53.3	56.1	50.0	54.7
9. Education					
Univ. Degree	24.3	24.8	21.2	15.0	26.9
College Degree	28.3	28.4	27.3	27.5	28.5
High School	38.9	37.7	45.5	45.6	37.0
Less than High School	8.6	9.0	6.1	11.9	7.6
10. Skills Trainig in Business Activity	30.8	31.1	29.5	17.6	35.0
11. Self-employment training	40.9	42.2	34.7	43.8	40.1

Table 2 - Business and Survey Characteristics[38]

all figures in percentage terms unless otherwise noted	All Clients (n=1064)	Group Clients (n=902)	Individual Clients (n=162)	Delinqeunt Clients* (n=258)	Paid Clients* (n=806)
Business Characteristics					
1. Other Sources of Credit	60.8	62.1	54.2	45.4	656.2
2. Startup Busienss	36.9	37.5	33.6	44.0	34.7
3. Busiess Location					
Home	74.5	75.9	66.4	69.5	76.1
Store/Shop/Other	25.5	24.1	33.6	30.5	23.9
4. Monthly Revenues ($)	3073	2578	5887	3753	2878
5. Monthly Profits ($)	1082	845	2392	1525	959
6. Monthly Household Income ($)	1511	1449	1826	1325	1567
7. Household Income	16.3	16.9	12.5	13.6	17.0
/ Loan Payment	(13.0)	(13.5)	(10.9)	(10.9)	(13.8)
8. Business Revenue	26.8	26.1	32.9	30.0	26.1
/ Loan Payment	(16.8)	(16.6)	(20.9)	(19.6)	(16.4)
9. Buiness Profit	9.6	8.8	15.9	14.9	8.3
/ Loan Payment	(6.6)	(6.6)	(5.5)	(7.2)	(6.4)
Telephone Survey Data					
10. Proportion of group known well before Calmeadow					
	0.56	0.56	na	0.42	0.57
11. How much trust existed within group					
A Great Deal	53.8	53.8	na	40.5	53.3
Some	31.4	31.4	na	33.3	31.4
Little	10.6	10.6	na	14.3	9.8
None	3.0	3.0	na	2.4	3.2
Don't Know	1.2	1.2	na	9.5	2.2
12. Motivations for repayment: Do you want to let group down					
Extremely Important	81.0	81.0	na	64.3	81.1
Important	14.1	14.1	na	33.3	12.8
Somewhat Important	3.7	3.7	na	0.0	4.2
Not Important	1.2	1.2	na	2.4	1.9
13. Are you member of team, club, association or organization					
Yes	49.0	48.8	48.0	30.0	51.3
No	51.0	51.2	52.0	69.7	48.7

Table 3 - Probit Marginal Effects Estimates of the Effect of Peer Group Lending on the Probability of Default[39]

	Peer Group Dummy Only (1)	Household, Demographic Only (2)	Household Demographic, Business, institutional, Neighborhood, Cluster Effects (3)	Household Demographic, Business, Institutional, Neighborhood, Cluster Effects, Narrow Default Definition (4)
Peer Loan	-0.2247* (0.0502)	-0.2100* (0.0517)	-0.1688* (0.0730)	-0.0866** (0.0590)
Not Married		0.0630** (0.0321)	0.0837* (0.0306)	0.0806* (0.0235)
Male		0.0548** (0.0315)	0.0472 (0.0313)	0.0377 (0.0249)
Technical Training		-0.1135* (0.0308)	-0.0956* (0.0323)	-0.0802* (0.0251)
Source of Outside Credit			-0.0905* (0.0326)	-0.0723* (0.0267)
Startup			0.0691* (0.0348)	0.0626* (0.0281)
Home Based Business			-0.0954* (0.0373)	-0.0872* (0.0319)
Ln Profits			-0.0048 (0.0062)	-0.0010 (0.0055)
Loan Size			0.0159** (0.0090)	0.0080 (0.0069)
N	702	702	702	702
LR chi2	23.97	83.12	122.16‡	76.46‡
Pseudo R2	0.0319	0.1102	0.1746	0.1601

Table 4 - Probit Marginal Effect Estimates of the Probability of Entering a Peer Group Loan Program[40]

	Household Income (1)	Household Income, Age (2)	Household Income, Revenue (3)	Household Income, Age, Revenue (4)
Household Income [High Income Excluded]				
None	0.0959* (0.0286)	0.0787* (0.0308)	0.0970* (0.0284)	0.0803* (0.0304)
Low	0.1038* (00295)	0.0924* (00291)	0.1028* (00294)	0.0916* (00290)
Middle	0.0616** (0.0282)	0.0519** (0.0285)	0.0586** (0.0280)	0.0488 (0.0284)
[Age<30 excluded]				
Age 31-40		0.0266 (0.0400)		0.0274 (0.0402)
Age 41-50		0.0207 (0.0399)		0.0211 (0.0400)
Age 51-60		0.0823* (0.0336)		0.0836* (0.0331)
Age 61+		0.1367* (0.0214)		0.1359* (0.0215)
Ln Revenues			-0.0076 (0.0066)	-0.0080 (0.0063)
N	894	894	894	894
Wald chi2	166.43	181.86	167.21	181.48
Pseudo R2	0.4096	0.4343	0.4115	0.4365

TABLE 5 - MATCHING ESTIMATES OF THE EFFECT OF PEER GROUP LENDING ON THE PROBABILITY OF DEFAULT[41]

	Peer Group Dummy Only†		Full Specification†	
	w/o replacement (1)	with replacement (2)	w/o replacement (3)	with replacement (4)
	Peer Loan Estimates			
No trimming	-0.6371* (0.1524)	-1.0381* (0.0717)	-0.4521 (0.3910)	-0.4859* (0.1373)
5% Trimming	-0.6572* (0.1932)	-1.1072* (0.0826)	-0.4789 (0.3659)	-0.5523* (0.1482)
10% Trimming	-0.6727* (0.1873)	-1.2001* (0.0917)	-0.5264 (0.3441)	-0.6784* (0.1496)
15% Trimming	-0.6789* (0.1804)	-1.2067* (0.0846)	-0.5092 (0.3568)	-0.6961* (0.1624)

TABLE 6 - ROBUSTNESS CHECK: THE EFFECT OF PEER GROP LENDING ON THE PROBABILITY OF DEFAULT WITHIN GROUP TRUST AND LOAN SIZE SUB-GROUPS[42]

	High Trust Groups Excluded (1)	Low Trust Groups Exclded (2)	Loan Size <=$1,000 (3)	Loan Size <=$2,000 (4)
	Peer Loan Coefficients			
1.Probit - Peer Dummy Only† Group	-0.1682* (0.0420)	-0.1999* (0.0430)	-0.3634* (0.0849)	-0.2742* (0.0605)
2.Probit - Full Specification†, CE	-0.1396** (0.0748)	-0.1885* (0.0754)	-0.2773* (0.1295)	-0.1843* (0.0905)

Notes

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1 MFIs are organizations (typically non-profit) providing financial and social intermediation services to low-income individuals, including the self-employed. Financial services include credit and savings while social intermediation services include such things as group formation, training in financial literacy and development of management capabilities. The Grameen Bank (Bangladesh), BancoSol (Bolivia) and Bank Raykat (Indonesia) are commonly cited examples of MFIs. See Jonathan Morduch, "The Microfinance Promise," *Journal of Economic Literature* 37, (1999): 1569-1614.

2 Christian Ahlin and Robert M. Townsend, "Using Repayment Data to Test Across Models of Joint Liability Lending," (working paper, University of Chicago, February 2005). Available at: cier.uchicago.edu/papers/2006/ahlin-repayment-110705.pdf (accessed June 23, 2008).

3 Specifically, we find that there are characteristics that lower the likelihood of default, which are also correlated with being in a peer group program, but that this positive selection into the program, which reduces the magnitude of the peer loan effect in some estimates by approximately 50 percent, does not eliminate its significance. We take this as an indication that borrower effort is one of the primary channels by which group lending leads to better borrower repayment performance.

4 See Ghatak (2000), Laffont and N'Guessan (2000), Ghatak and Guinanne (1999), van Tassel (1999), De Aghion and Gollier (1998), Besley and Coate (1995), Stiglitz (1990) and Varian (1990)

5 Ghatak, "The economics of lending with joint liability: theory and Practice;" Murdoch, "The Microfinance Promise."

6 The theoretical models of Stiglitz (1990), Varian (1990), Banerjee and Guinanne (1994) and Aghion (1999) draw heavily on this concept.

7 Ghatak and Guinnane, "The Economics of Lending with Joint Liability: theory and practice."

8 Beatriz Armendáriz de Aghion and Jonathan Morduch, "Microfinance Beyond Group Lending," *Economics of Transition* 8, no 2 (2000): 224-243.

9 A. Diagne et al, "Design and Sustainability Issues of Rural Credit and Savings Programs for the Poor in Malawi: An Action-oriented Research Project,"*Report prepared for Irish Aid, Development of Foreign Affairs, Government of Ireland*, 2000.

10 Ghatak and Guinanne (1999) note that "there is little empirical evidence on the relative importance of joint liability as opposed to other program features", such as direct monitoring on the part of the lender. Ghatak and Guinnane, "The economics of lending with joint liability: theory and practice."

11 Joint liability is not the only operative feature of group lending, as there may be other mechanisms at work such as risk pooling, spillover effects and the ability of lenders to lower transaction costs. Likewise, many MFIs employ other innovative lending techniques that can improve repayment performance, such as more timely repayment schedules and dynamic incentives.

12 Ahlin and Townsend (2003) find that lower interest rates, lower joint liability payments and higher levels of human capital are correlated to higher repayment rates. Ahlin and Townsend, "Using Repayment Data to Test Across Models of Joint Liability Lending."

13 Dean Karlan, "Social capital and group banking," *Princeton University*, 2003.

14 Bruce Wydick, "Can social cohesion be harnessed to repair market failures? Evidence from Group lending in Guatamala," *Economic Journal* 109, no. 457 (July 1999): 463-475.

15 Mark Wenner, "Group Credit: A Means to Improve Information Transfer and Loan Repayment Performance," *Journal of Development Studies* 32, no. 2 (December 1995): 264-281.

16 Many commercial fixed term loans (such as mortgages) typically contain penalties–or restrictions—for early repayment.

17 Despite being in a peer-group loan program, all borrowers operate their own individual businesses.

18 This requirement is explicitly stated in the "Borrower's Warrant" and is repeatedly emphasized in Calmeadow's promotional literature. Furthermore, when peer group clients fall into arrears, they are

reminded that their behavior will result in their fellow group member's inability to access future loans.

[19] Unlike many MFIs, Calmeadow does not means test its clients – any individual may, regardless of their socio-economic well-being (unlike the Grameen Bank, for instance, which prevents wealthier individuals from applying), can apply for a loan.

[20] The business age criterion is occasionally relaxed if the individual has self-employment training (i.e., any formal technical education on how to run a small business).

[21] The majority of the borrowers in the sample accessed their loans from 1996 to 1999 and this was a period of considerable macroeconomic stability in the Metro Toronto and Halifax areas.

[22] GMS is a loan-tracking software package used by commercial lenders. The use of this software package reinforces the notion that Calmeadow was committed and able to apply commercial lending standards to their balance sheet.

[23] The survey data covers a more limited sample of the data, reducing the sample to 537 borrowers.

[24] For the purposes of this study, default is defined as any loan that had been "written off," has been sent to a collection agency, or the loan is "non-performing." Non-performance includes any loan where 3 or more payments have been missed. The definition of default used in this study conforms to the commercial banking standard of "non-performance" and provides a truer picture of repayment performance.

[25] While seemingly high by conventional banking standards, the question of whether the arrears rate at Calmeadow is comparable to the average rate as reported by most North American MFIs is an open one. The reason is that many MFIs have never provided officially published/independently audited organizational statistics on default rates. This reporting difficulty is not confined to North American MFIs. For instance, Morduch (1999) has shown that the Grameen Bank, despite being one of microfinance's flagship programs, consistently underreports its default rates at the institutional level. It is easy to imagine that local loan managers would have equally great incentives to underreport arrears rates at the individual or group level. For a detailed discussion as to why the Grameen Bank may understate its default rate, see Murdoch, "The Microfinance Promise."

[26] For a discussion of the effects of social capital, as measured by membership in civil society, on the performance of microfinance borrowers see: Rafael Gomez and Eric Santor, "Membership has its Privileges: the effect of social capital and neighborhood characteristics on the earnings of microfinance borrowers," *Canadian Journal of Economics* 34, no.4 (November 2001): 943-966.

[27] Unbiased estimates of can still be obtained if the sources of self-selection occur over observable characteristics.

[28] James Heckman and Jeffrey Smith, "Experimental and non-experimental evaluations," International Handbook of Labour Market Policy and Evaluation, ed. Gunther Schmid et al., (London: Edward Elgar, 1996).

[29] William H. Greene, Econometric Analysis, (Upper Saddle River, NJ: Prentice Hall, 2000)

[30] This is because estimates of program effects assume that the impact of the program can be captured entirely by the single index ?X, which may not be related to the borrower's propensity to participate in the program. Furthermore, simple probit regression implies a common program effect across all borrowers. However, if the treatment group responds differently to the treatment then the standard treatment effects model does not resolve these differences.

[31] Ideally, one would like to conduct a randomized experiment to estimate the effects of group lending. Unfortunately, MFIs have been unwilling to conduct such experiments, but may be more likely to do so in the future. See the work of the Poverty Action Lab, www.povertyactionlab.com.

[32] Paul Rosenbaum,and Donald Rubin, "The central role of the propensity score in observational studies for causal effects," *Biometrika* 70 (April 1983): 604-20.

[33] John C. Ham, Xianghong Li, and Patricia B. Reagan, "Matching and Selection Estimates of the Effect of Migration on Wages for Young Men," (Working paper, Ohio State University, Department of Economics, 2006).

[34] Table 3 column [3] for coefficients not shown, also reveals that institutional and neighborhood level effects are important. It terms of the former, it appears that screening and direct monitoring by individual loan managers matters. While the individual coefficients are not significant, they are jointly significant. In terms of neighborhood effects, borrowers living and or working in certain neighborhoods outperform their counterparts. This finding is in keeping with the peer group literature, which claims that social norms are

more operative in tightly knit communities. In our data, the fact that a negative co-efficient appeared in areas of the city which were built prior to 1960 and which were classified as urban (rather than suburban) by Statistics Canada, lends credence to the above interpretation.

35 Huber\White\sandwich estimators of the variance are utilized.

36 Unlike most applications of matching methods, there are more treatment units than control units. Estimating the model with individual loans as the "treatment", so that there are more control units than treatment units does not change the results. It should also be noted that group borrowers were older, had lower income and home based businesses. Interestingly, certain loan mangers were more likely than others to grant group

37Household Income/ Loan Payment represents the ratio of average household income to monthly loan payment. The "default rate" is the percentage of borrowers whose loans have been "written off", written off and in "collections", and "non-performing". * "Paid" refers to clients who successfully repaid their loans, "delinquent" refers to those borrowers who defaulted on their loan. Numbers in parentheses ( ) indicate median. *Includes all current singles at time of survey and hence includes ever-married (widowed, separated, divorced).

38"Paid" refers to clients who successfully repaid their loans; "delinquent" refers to those borrowers who defaulted on their loan. Numbers in parentheses ( ) indicate median.

39*Indicates significance at the 5% level, **indicates significance at the 10% level. (Standard errors in parentheses) ‡ indicates Wald Chi2 test statistic. Column (2) includes controls for education, income and immigrant status. Column (3) includes controls for education, income, loan manager and neighborhood effects.

40 *Indicates significance at the 5% level, **indicates significance at the 10% level, clustered standard errors in parentheses. Controls for education, income, immigrant status, loan manager and neighborhood effects are included.

41*Indicates significance at the 5% level, **indicates significance at the 10% level. Bootstrapped standard errors,1000 reps in parentheses. † Peer group Dummy refers to the model estimated in column [1] Table 3, and the Full specification refers to the model estimated in column [4], Table 3

42*Indicates significance at the 5% level, **indicates significance at the 10% level, standard errors in parentheses. † Probit-Peer Group Dummy refers to the model estimated in column [1] Table 3 and Probit-Full Specification refers to the model estimated in column [3] Table 3