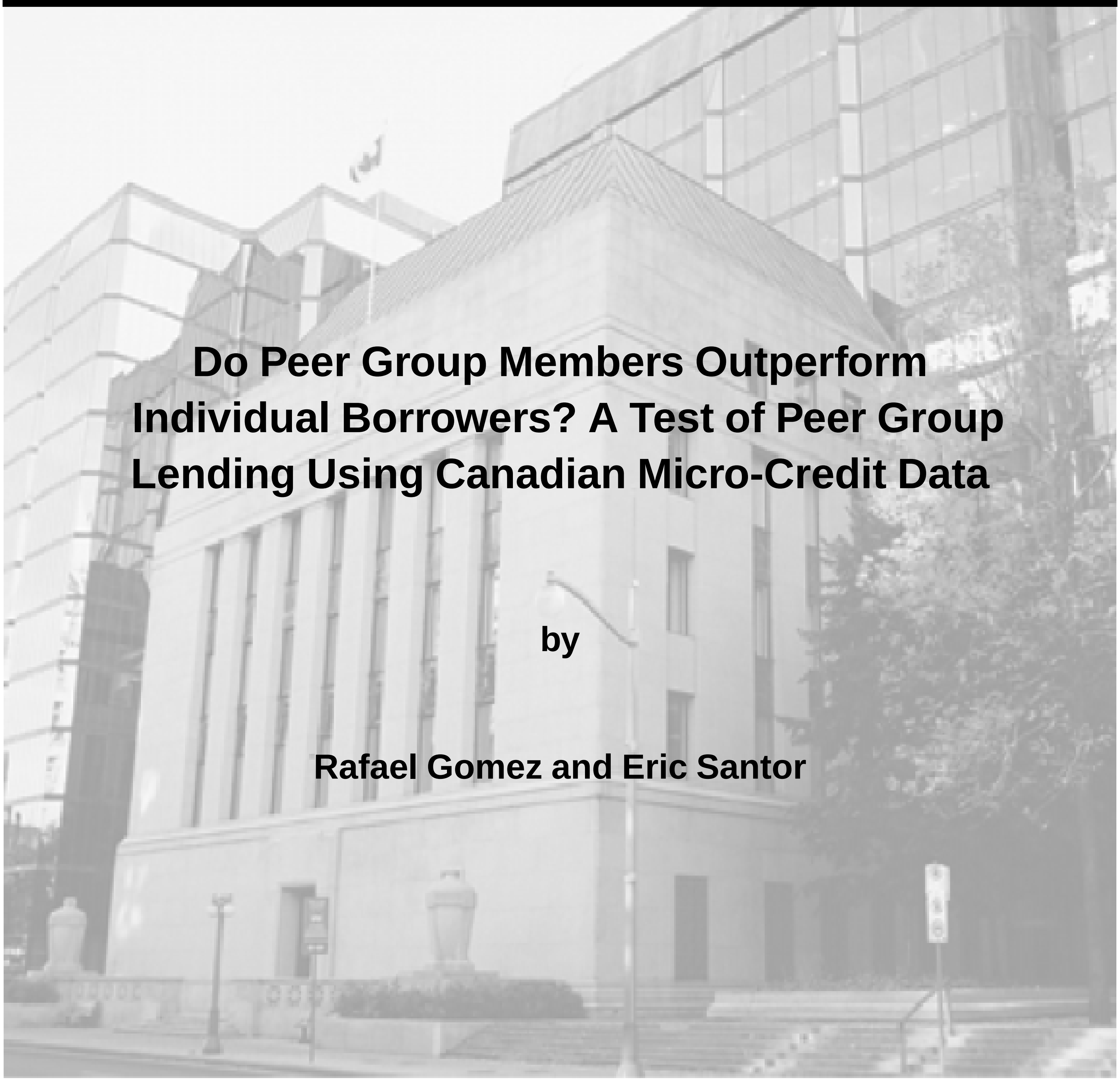
Bank of Canada Banque du Canada

Working Paper 2003-33 / Document de travail 2003-33



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ISSN 1192-5434

Printed in Canada on recycled paper

Bank of Canada Working Paper 2003-33

October 2003

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Acknowledgements

We would like to thank Dwayne Benjamin, Albert Berry, Jon Cohen, Martin Connell, David De Meza, Morley Gunderson, Sonia Laszlo, Kevin Milligan, Jim Pesando, Konstantinos Tzioumis, and the staff of Calmeadow Metrofund and Calmeadow Nova Scotia for assistance and helpful comments. Financial support was provided by the Social Science and Humanities Research Council and the Canadian Employment Research Forum.

Abstract

Microfinance institutions now serve over 10 million poor households in the developing and developed world, and much of their success has been attributed to their innovative use of peer group lending. There is very little empirical evidence, however, to suggest that group lending schemes offer a superior institutional design over lending programs that serve individual borrowers. The authors find empirical evidence that group lending does indeed lower borrower default rates more than conventional individual lending, and that this effect operates through the dual channels of selection into the peer lending program and, once inside the program, greater group borrower effort.

JEL classification: J23, O17, E82
Bank classification: Development economics

Résumé

Les institutions de microfinance prêtent aujourd'hui des fonds à plus de 10 millions de ménages pauvres dans les pays en développement et les pays développés. Leur succès est en grande partie attribué au fait qu'elles recourent à une forme originale de prêt collectif. Il existe cependant très peu d'éléments empiriques attestant que ces mécanismes soient mieux conçus que les programmes de prêt aux particuliers. Les auteurs obtiennent des résultats empiriques qui montrent que les participants aux programmes de prêt collectif présentent un taux de défaillance moins élevé que les emprunteurs individuels, et que ce phénomène est dû à la fois à la sélection opérée au départ et aux efforts accrus que les membres d'un groupe d'emprunteurs déploient.

Classification JEL : J23, O17, E82
Classification de la Banque : Économie du développement

1. Introduction

Microfinance institutions (MFIs) now serve over 10 million households worldwide and are expanding throughout the developing and developed world.[1] Despite the relative poverty of their clients, MFIs have been able to extend credit to poor households through the innovative use of group lending, while maintaining high repayment rates and financial sustainability. Practitioners and pundits attest to the ability of group lending to increase incomes, consumption, and the stock of human capital of households that lack collateral and face severe credit constraints. Not surprisingly, the apparent success of peer group lending has drawn the attention of economists from both theoretical and applied perspectives.

This paper addresses two empirical questions that remain largely unanswered in the economics literature: (i) does peer group lending lead to higher repayment rates than traditional individual lending techniques, and (ii) is the beneficial peer group effect the result of greater borrower effort or the consequence of positive self-selection into the group lending program? These two questions lie at the heart of the microfinance debate and therefore warrant close empirical scrutiny. An affirmative answer to the first question, for example, would explain why group lending schemes are instituted in the first place, whereas a positive response to the second question would confirm theoretical and practitioner claims that peer groups not only perform a useful sorting function but provide positive spillovers to all those enrolled in such programs, by inducing higher levels of borrower effort.

Utilizing data from two North American microfinance institutions, we find evidence that those enrolled in group loan programs outperform individual borrowers in terms of default probabilities. We attribute this effect to the dual channels of sorting and incentives for greater effort once inside the group. Employing both self-selection and matching methods estimates, we find that there are unobserved characteristics that lower the likelihood of default, and that they are correlated with being in a peer group program. However, this positive selection into a peer group program—though it reduces the magnitude of the peer loan probit results by roughly 20 per cent—does not eliminate the significance of the peer group effect, which indicates that greater effort (not sorting) is the dominant channel by which group lending improves borrower performance.

This paper is organized as follows. Section 2 outlines the central theoretical and empirical claims and reviews the relevant literature that shows that peer group lending is a superior institutional mechanism compared with conventional individual lending techniques. Section 3 describes how the data were collected and presents descriptive statistics. Section 4 describes the empirical

1. The Grameen Bank in Bangladesh, BancoSol in Bolivia, and Bank Raykat Indonesia are the most commonly cited examples of MFIs. See Morduch (1999) for a brief review of these institutions.

methodology used. Section 5 provides the empirical results. Section 6 offers conclusions and identifies areas of further research.

2. Why Should Peer Group Members Outperform Individual Borrowers?

In recent years, considerable effort has been made to understand both how group lending works and the effect it may have in practice. Most studies have focused on how peer group schemes can overcome the inherent problems associated with asymmetric information in financial markets.[2] 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 (Morduch 1999; Ghatak and Guinnane 1999). Group lending with joint liability overcomes these problems by passing the monitoring activity on to the borrowers themselves. The idea is that group members will monitor their peers and pressure those individuals who misuse their loans to act accordingly.[3] While this monitoring activity is costly for the borrower, it is assumed to be much less so than for the lender, since group members will typically know each other well in advance of the date of borrowing.[4] Assuming that monitoring costs are low and social sanctions effective, Ghatak and Guinnane (1999) show that, compared with an individual liability contract, effort will be strictly higher under joint liability.[5] The implications of these findings also agree with the results reported in the personnel economics literature, which show that team-based production can have both sorting and incentive effects and that peer pressure within a team can have a discernible impact on worker effort and individual output (Lazear 1999).

Theoretical models, therefore, demonstrate that peer group schemes tend to induce higher levels of effort by borrowers due to intrapersonal monitoring and peer pressure. Although it is true that closer monitoring and increased effort is inherently difficult to measure, the consequences of such peer group effects are easier to observe: group members should outperform individual borrowers in terms of repayment success (holding all else constant).[6] We seek to measure this basic outcome

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2. See, for example, Ghatak (2000), Laffont and N'Guessan (2000), Ghatak and Guinnane (1999), van Tassel (1999), Armendariz de Aghion and Gollier (1998), Stiglitz (1990), and Varian (1990).
3. The theoretical models of Stiglitz (1990), Varian (1990), Banerjee, Besley, and Guinnane (1994), Conning (2000), and Armendariz de Aghion (1999) draw heavily on this concept.
4. The cost of monitoring for group members should be relatively low if one accepts that assortative matching occurs.
5. The effectiveness of peer group lending depends heavily on the notion that there is a long-run relationship between borrowers. If borrowers do not have a close relationship to their fellow borrowers, social sanctions would not be effective. In this sense, group lending is a repeated game.
6. Joint liability is not the only operative feature of group lending; 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.

and, if possible, to distinguish the incentive effects of group lending from any of the advantages brought about by sorting and self-selection into the peer group program.

2.1 Previous empirical literature

Despite the strong predictions of group lending models, there is little or no direct empirical evidence to suggest that peer group members actually outperform individual borrowers.[7] 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. Although much of their evidence confirms the predictions of theory, they find evidence that proxies for strong social ties, group monitoring, and group co-operation are negatively related to repayment.[8] On the other hand, Karlan (2003) shows that higher levels of social capital are positively correlated with repayment, particularly when facilitated by the appropriate environment. Wydick (1999a) suggests that groups matter, in that greater levels of social cohesion (such as knowing group members prior to group formation or living in the same neighbourhood) lead to lower levels of individual default. Wenner (1995) offers similar evidence that socially cohesive groups have higher repayment rates. Although many of the key predictions of group lending have been confirmed, no published study has yet compared individual borrower outcomes with those of comparable group members. Therefore, despite growing empirical evidence, two principal theoretical conjectures concerning peer groups remain unanswered: (i) whether group lending leads to lower default rates than individual lending techniques, and (ii) whether this effect is the result of positive selection into the peer group program or the result of greater borrower effort.

3. The Data

3.1 Sample considerations

The effectiveness of group lending, as predicted by the theoretical models noted earlier, would ideally be tested using a randomized experiment.[9] That is, to avoid problems of self-selection, one would like to run an experiment where borrowers are randomly placed into group and individual

7. Ghatak and Guinnane (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.
8. 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.
9. See Heckman and Smith (1996) for a discussion of the advantages and disadvantages of randomized experiments in assessing program effectiveness.

loan programs and the respective treatment and control group's loan-repayment performance are assessed. To date, MFIs have been unwilling to conduct such experiments and therefore one must resort to non-experimental regression techniques.

Not surprisingly, non-experimental techniques require rich data to test whether group lending with joint liability leads to higher repayment rates. The MFI from which data might be drawn must possess the following three attributes: (i) provision of group and individual loans, (ii) an accurate record of loan repayment, and (iii) a detailed profile of their borrower's characteristics. Very few MFIs, if any, offer both group and individual loans, collect sufficient client data, and accurately assess the true rate of borrower default.[10] This lack of data can be attributed to intrinsic features of the microfinance world.[11]

Fortunately, the data collected for this study, which are drawn from two MFIs—Calmeadow Metrofund (located in Toronto) and Calmeadow Nova Scotia (located in Halifax)—provide an opportunity to test the predictions of the theoretical models discussed above. Calmeadow provides data on both group and individual loans, maintains accurate records of client loan-repayment performance and collects a wide range of client information, including demographic, household, and business characteristics.[12] Appendix A provides a brief description of Calmeadow's institutional features, and highlights the advantages of the data.

3.2 Sample characteristics[13]

The data consist of 1,389 borrowers who accessed loans from Calmeadow Metrofund and Calmeadow Nova Scotia. There are 995 group and 394 individual borrowers, who represent the entire population of Calmeadow clients from 1 January 1994 to 30 August 1999.[14] For each borrower, demographic, business, and household data are extracted from the loan application contained in Calmeadow's client file, and repayment history is gathered from the GMS loan-

10. For instance, Morduch (1999) shows 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 Morduch (1999).
11. First, many MFIs lack the resources to collect such detailed data and, second, they may have only rudimentary accounting systems or alternative agendas (such as satisfying donors) that may make it difficult to obtain information on clients, repayment rates, and loan arrears.
12. Calmeadow transferred its micro-lending operation to the MetroCredit Union in January 2001. Loan repayment history is tracked through GMS, a software package designed specifically for financial lending institutions.
13. All descriptive results are given in Tables 1 to 6.
14. The majority of the borrowers in the sample accesssed their loans from 1996 to 1999 and this was a period of considerable macroeconomic stability in the Metropolitan Toronto and Halifax areas.

tracking system. The data have been supplemented by a telephone survey (conducted by the authors in July 1998 and available from them upon request) that measured borrower attitudes towards repayment and other normally hard-to-observe characteristics, such as the nature and abundance of social ties. The following subsections provide descriptive statistics of Calmeadow's clients, placing particular emphasis on the differences between group and individual borrowers, and successful and delinquent borrowers.

3.3 Statistics on default rates and loan terms

The default rate for Calmeadow borrowers is fairly high by microfinance standards, but not outrageously so.[15] The data reveal that roughly 21.2 per cent of all group borrowers and 41.4 per cent of all individual borrowers have defaulted on their loans. Likewise, 38.4 per cent of group borrowers and 88.7 per cent of individual borrowers have an "NSF" recorded on their loan (NSF implies a missed payment). In terms of the ratio of write-offs to outstanding loan portfolio, the arrears rate is approximately 8 per cent. While seemingly high by conventional banking standards, the arrears rate at Calmeadow is similar to the average rate reported by most North American MFIs.

Group loans range from $500 to $5,000 and individual loans range from $1,000 to $15,000, with mean and median loan sizes of $1,031 and $1,000 for group loans and $3,954 and $2,700 for individual loans, respectively. Loan terms vary from 6 to 24 months for group loans; individual loans offer longer terms to a maximum of 60 months. The cost of both types of loans is 12 per cent plus an up-front administration fee of 6.5 per cent. Loan payments average $95 per month for group borrowers and $220 per month for individual borrowers. Group loans are typically used for working capital, while individual loans are often used for working capital and/or the purchase of fixed assets.

3.4 Demographic, household, and business characteristics of borrowers

Calmeadow's clients are demographically diverse and representative of the population of Toronto and Halifax.[16] Approximately 52 per cent of all clients are female and 39 per cent are immigrants,

15. For this study, default is defined as any loan that has been "written off," sent to a collection agency, or is "non-performing." Non-performance includes any loan where three 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 reasonably accurate picture of repayment performance.
16. The notable difference between the Toronto and Halifax borrowers is that Halifax clients are predominantly native-born Caucasians, with a significant Canadian-born African-Canadian minority. Only 10 per cent of Halifax borrowers are immigrants. Apart from differences in ethnic composition and immigrant status, the two groups are virtually the same across most observable characteristics.

51 per cent are white, and most major ethnic groups are present (Tables 2a and 2b). The sample is more heavily weighted in favour of African-Canadians, however, and East- and South-Asian Canadians are underrepresented.[17] The average borrower is 43 years old, with two dependants and more education than the general population (over 52 per cent have post-secondary school diplomas or degrees). The majority of Calmeadow Metrofund's borrowers live in the city of Toronto, and its remaining clients are dispersed across the Metropolitan region. Likewise, half of all Calmeadow's Nova Scotia clients live in the Halifax-Dartmouth area, and the remainder reside in various small communities scattered across Nova Scotia.

Table 3 highlights the extent to which Calmeadow serves credit-constrained clients. The majority of clients, while obviously credit constrained, nevertheless have other sources of credit (primarily in the form of credit cards). However, 39 per cent rely solely on Calmeadow for their funds. Of the 86 per cent of clients who have a credit history, the median credit limit is $2,722 and the median net limit (credit limit less outstanding balance) is only $62. Consequently, the median credit utilization rate is 98 per cent. Likewise, significant portions of Calmeadow clients have a poor credit history: 10 per cent have previously declared bankruptcy, 13 per cent have debt obligations sent to a collection agency, and 40 per cent have had at least one “R9,” a debt that has been written off by the credit grantor. Overall, roughly 46 per cent of all borrowers have “bad credit.” Consequently, one can assume that Calmeadow is serving clients who cannot access credit (or further credit) from conventional sources.

The household characteristics reveal that the average Calmeadow client is poor. Average monthly non-business household income is $1,510 (median $1,200) and net worth is only $10,930 (median $4,620) (Table 4).[18] Many clients (49 per cent) have a wage or salary income and 27 per cent receive some kind of government assistance. Roughly half of all clients do not work in paid employment, and 40 per cent cite self-employment income as their “major” or “only” source of income.

The average business operated by a Calmeadow client is very small, with monthly revenues of only $3,239 (median $1,700) and monthly profits of $1,110 (median $600) (Table 5). The vast majority of clients run sole proprietorships located in their home, over 37 per cent are start-ups (less than one year in operation), and existing businesses have been operating for an average of two years. The businesses cover a wide range of activity, but most provide some form of personal, business, or retail service. A small but significant minority of businesses manufacture small items

17. This may represent the fact that South- and East-Asian Canadians (in particular) have well-developed informal credit markets within their ethnic community and thus Calmeadow is not an attractive source of credit.

18. This figure is likely biased upwards significantly. Anecdotal evidence suggests that, while liabilities are well reported (due to their verification), assets are systematically overestimated.

(artisanry or jewelry manufacturing, for example) or own construction/landscaping businesses. Apart from this last category, most businesses are similar in size and composition.

3.5 Group versus individual borrowers

There are several key demographic differences between group and individual borrowers. Group borrowers are more likely to be female, of Hispanic ethnicity, and immigrants, while individual borrowers are more likely to be of African ethnicity, male, and born in Canada (Table 2a). Individual borrowers have less education but more skills training related to their business activity. With respect to household characteristics, individual borrowers have higher incomes and assets but similar net worth, rely more heavily on their self-employment income, and are less likely to receive government assistance. Although there are still many start-ups, individual borrowers have larger and older microenterprises than group borrowers (monthly revenues of $5,889 compared with $2,579) and higher profit levels. Likewise, individual borrowers run proportionately more storefront locations and are more likely to be incorporated.

3.6 Delinquent versus successful borrowers

There are significant differences between borrowers who successfully repay their loans and those who fail to fulfill their obligations to Calmeadow Metrofund. 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. 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. Demographically, delinquent borrowers tend to be single, male, and born in Canada, with less education and significantly lower levels of business-related skills training. Household income, assets, and net worth are slightly lower, but statistically similar. Delinquent borrowers lack outside sources of credit: for those who do have credit, their “credit utilization” rate is higher and they are more likely to have a poor credit history. In terms of business type, there are only a few differences in terms of activity, revenues, profits, and ownership type. Delinquent businesses, however, tend to be start-ups located outside the home.

Within the groups themselves, attitudinal differences appear in the survey data. Delinquent borrowers are less likely to feel a moral obligation to repay their loans (Table 6). Individuals who have known their fellow members before forming the peer group are less likely to default. Likewise, default is less likely if a great deal of trust exists in the group or if group members feel a moral obligation to their peers. Lastly, individuals who have “social capital” are less likely to default, since individuals who belong to an association, club, or sports team report higher repayment rates.[19]

4. Empirical Specifications

4.1 The standard regression estimation

The descriptive statistics reveal that there are important demographic, household, and business differences between those borrowers who default on their loan and those who successfully repay. Utilizing this information (and one can imagine that loan managers do so less formally to allocate loans), one can form a prediction regarding the likelihood of default based upon demographic, household, and business characteristics. This credit-scoring approach can follow several functional forms, including linear discriminant analysis, logit/probit regression, or, as applied more recently, neural net learning techniques. In practice, credit scoring has relied heavily on the first two methods, with a bias towards utilizing logit/probit techniques (Thomas 2000).

More specifically, a credit-scoring model[20] that could be used to assess the effect of group membership would first propose that there is an index function with a latent regression,

$$D_i^* = \beta X_i + \varepsilon_i , \tag{1}$$

where the dependent variable, D^*, is the propensity to default and i indexes over the individual. The likelihood of default is a function of X_i, a set of borrower characteristics that includes income, home ownership status, employment records, and credit history; other demographic, household, and business, and neighbourhood and institutional characteristics; and a dummy variable that indicates peer group membership.[21] The probability of default can thus be expressed as

$$P_i = \mathrm{Prob}[D_i = 1 | X_i] .$$

Given that ε has the standard properties (normally distributed with mean 0 and variance 1), the default probability is,

$$\mathrm{Prob}[D_i = 1 | X_i] = \Phi(\beta X_i) , \tag{2}$$

19. For a discussion of the effects of social capital, as measured by membership in civil society, on the performance of microfinance borrowers, see Gomez and Santor (2001).
20. This section follows Greene (1998).
21. Institutional-level characteristics include which MFI manager screened the applicant and monitored the loan.

where $\Phi(\bullet)$ is the standard normal cumulative distribution function. This allows one to estimate the following probit model:

$$D_{ig} = \alpha + \beta X_{ig} + \theta G_{ig} + \varepsilon_{ig}, \tag{3}$$

where D_{ig} is a discrete binomial variable ($D_{ig} = 1$ indicates that the borrower defaults, 0 otherwise), and the subscript *i* indexes over the individual while *g* indexes over the group. The matrix of borrower characteristics, *X*, group level characteristics, and a dummy variable, *G*, indicate that the borrower is a member of a peer group. The error term, ε_{ig}, has the standard properties. The key prediction of group lending with joint liability can be assessed within this regression framework. That is, do group borrowers outperform individual borrowers with respect to loan repayment?

A second specification based on a standard regression framework can also be utilized, where the dependent variable is the amount of the loan written off, L_{ig}. This is done to examine whether group lending mitigates not only the likelihood of default, but also the severity of default. Therefore, we also estimate the following Tobit model,

$$Y^*_{ig} = \alpha + \beta X_{ig} + \theta G_{ig} + \varepsilon_{ig}, \tag{4}$$

$$Y^*_{ig} = \{0 \; if \; Y_{ig} \le 0; Y_{ig} \; if \; Y_{ig} > 0\}, \tag{5}$$

where Y_{ig} is a latent variable that is a continuous measure of the loan write-off, *X* is the matrix of borrower characteristics that is equivalent to the specification in (3), and the error term has the standard properties. Since Y_{ig} is truncated at zero for borrowers that successfully repay, the Tobit specification is warranted.

The hypothesis that group borrowers should outperform individual borrowers in terms of loan repayment can be tested by estimating models (3) and (4) for the entire sample of individual and group borrowers. If peer groups induce higher levels of borrower effort, then $\hat{\theta}$ should be negative and significant in both cases. Unfortunately, the empirical procedures described above are not so straightforward, as self-selection into the peer group program needs to be accounted for if we wish to identify whether the incentive effects of group lending are operative.

4.2 Isolating the incentive effects of peer group lending

A useful way of isolating the incentive channels in models (3) and (4) is to consider θ as the “treatment” effect of belonging to a peer group, while being an individual borrower indicates the absence of the treatment. 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 estimate of θ will provide an unbiased measure of the treatment (incentive) effect. In the case of Calmeadow's lending program, however, it is evident that participation is not exogenous, because only those borrowers who have large projects and sufficient collateral are able to access the individual loan program.[22] Consequently, one needs to determine how endogenous program participation will bias the results, and how this bias can be accounted for in the estimation procedure.

4.2.1 Estimation of non-experimental treatment effects

To account for endogenous program participation, a treatment-effects model can be estimated following Greene (2000). In this framework, one estimates the average impact of program participation as:

$$\theta = E(D_1 \mid \mathrm{G} = 1) - E(D_0 \mid \mathrm{G} = 0)\,, \tag{6}$$

where D_1 is the outcome if the treatment is taken up, and D_0 if not; $G = 1$ indicates that the borrower is eligible to take up the treatment, and $G = 0$ 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. However, 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, because estimates of program effects assume that the impact of the program can be captured entirely by the single index, ß*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. If the treatment group responds differently to the treatment, however, then these differences are not resolved by the standard treatment-effects model.

4.2.2 Why not a randomized experiment?

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

$$\theta_T = E(D_1 \mid \mathrm{G} = 1) - ED_0 \mid \mathrm{G} = 1)\,. \tag{7}$$

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22. Unbiased estimates of $\hat{\theta}$ can still be obtained if the sources of self-selection occur over observable characteristics (Heckman and Hotz 1989; Heckman and Smith 1996).

That is, one needs to observe the outcomes of the borrowers that received the treatment and compare them with 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 (7) does not exist in the data, since it is not observed.

A solution is for the researcher to create $E(D_0 \mid \mathrm{G} = 1)$ by implementing a randomized experiment: borrowers would apply to the group lending program and a proportion of those accepted would be randomly denied access. This would create a true control group analogue that could be used to determine the difference between the outcomes of those borrowers that accessed the program and the outcomes if the program had not existed. A randomized experiment, however, may not generate useful counterfactuals in this case, since one of the underlying mechanisms of group lending is endogenous group formation. While some group effects may be present in the randomized experiment, the underlying motivational factors that are attributable to social capital and assortative matching within the group would be omitted. Although randomized experiments have been successfully implemented in the presence of endogenous selection effects in certain settings, these approaches are not feasible here, since, as noted earlier, MFIs are unwilling to conduct such an experiment.[23] Therefore, other approaches need to be considered.

4.2.3 A matching-methods approach

In our case, a solution to this evaluation problem is to create the counterfactual $E(D_0 \mid \mathrm{G} = 1)$ by matching treatment and control borrowers along observable characteristics. For every borrower in the treatment, one can find an individual borrower who is identical in every respect, except for the availability of a group lending loan. Since there are many dimensions along which to match borrowers, finding comparable matches in any conventional way becomes difficult if not impossible.

Fortunately, there is a solution to this problem, known as "matching methods." Rosenbaum and Rubin (1983) show that, instead of matching along X, one can match along $P(X)$—the probability that the borrower participated in the treatment group—and thus estimate consistent and unbiased estimates of the effect of program participation on the treated. The advantages 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 (Ham, Li, and Reagan 2003).

23. A large literature has evolved around the use of randomized experiments to evaluate job training programs. See Heckman and Smith (1996) for a complete survey.

The ability of matching-method techniques to construct a suitable control-group sample analogue depends on the following crucial assumption:

$$E(D_0 | P(X), G = 1) = E(D_0 | P(X), G = 0). \tag{8}$$

That is, conditional on the propensity score, the outcome in the non-participation state is independent of participation. For this result to hold, Smith and Todd (2001) suggest that the data must possess the following criteria. First, the data for the control and treatment group must come from the same source; second, the outcomes must occur in the same geographic region; and third, the data must be “sufficiently rich” that (8) holds. The limitations of matching methods are a function of these conditions and, in particular, of the third criterion. The ability to create suitable counterfactuals to the treatment group depends on being able to match along observable characteristics. If the process of selection into the participation and non-participation states is a function of unobservables that are not captured by the observable data, then the control group may not be properly specified (Ham, Li, and Reagan 2003). In this sense, the limitation of utilizing the propensity score as a measure of “comparability” is determined by the availability of sufficient conditioning variables. If the decision to participate in the program is poorly measured, the treatment and control groups will be poorly matched, and any inferences on the effect of the “treatment on the treated” will be biased in an undetermined manner. In this way, matching may actually accentuate the biases caused by selection on unobservables (Smith and Todd 2001).

4.2.4 Is our data appropriate for a matching-methods approach?

Fortunately, the Calmeadow data are sufficiently rich that the sources of sorting and self-selection that place borrowers into group and individual loans are easily observable, because the requirements outlined in Calmeadow’s loan-application process formally determine the placement of borrowers (ex ante) into group or individual loans based on specific characteristics. For instance, to qualify for an individual loan, the borrower must have a business one year old or older, provide a sophisticated business plan, have self-employment training, and pledge collateral.[24] These criteria imply that individual borrowers will have larger businesses, more skills, and greater household resources than group borrowers. The data can control for these differences between borrowers, because there is information available on start-up status, business size, and household resources (in terms of household income and net worth). While the criteria

24. While the individual loan application states that collateral is necessary, this requirement is mostly symbolic. Typically, the security agreement utilizes the asset to be purchased as the collateral. Consequently, the collateral requirement is rarely, if ever, a barrier to accessing loans (this is reinforced by the fact that Calmeadow executed on a security agreement only once in the period covered by the sample).

that places a borrower into an individual or group loan appears limited, there are other characteristics that sort borrowers into the appropriate loan type. The requirement of a more sophisticated business plan indicates the need for differentially higher levels of human capital, while a longer loan term for individual borrowers suggests differential borrower-side risks. Given the extensive nature of the Calmeadow data, the potential biases stemming from the use of matching methods are greatly mitigated in this instance.[25]

5. Results

5.1 Does belonging to a peer group reduce borrower default?

To answer this key question, Table 7 reports the results from estimating model (3) by maximum likelihood. The effect of being in a group, when controlling for many typical variables, is negative with respect to loan defaults in all specifications, columns 1 through 4. Measured in percentage terms (Table 7, column 1), we find that group lending reduces the probability of default by roughly 17 per cent more than individual lending. When one controls for the size of loan and business characteristics (Table 7, column 3), this effect remains significant. The fact that the peer group dummy seems to matter even after one controls for the smaller loans and differential business characteristics of group borrowers (both factors that imply a lower degree of default risk) is indicative that peer groups seem to do more than sort borrowers. Lending even more validity to our results is the fact that the findings on our other variables of interest are consistent with many of the conventional results from the credit-scoring literature and anecdotal evidence from MFIs.[26] One preliminary interpretation of the above is that the anticipated effects associated with peer pressure and increased borrower effort appear to be an operative feature of the group-lending mechanism.

Table 7, column 3, also reveals that institutional and neighbourhood level effects are important. In terms of the former, it appears that screening and direct monitoring by individual loan managers matters. Although the individual coefficients are not significant, they are jointly significant (results not shown). In terms of neighbourhood effects, borrowers living and or working in certain neighbourhoods 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

25. Interestingly, the observable criteria that lead to rejection for many loan applications, more often than not, do not appear to be substantially different between group and individual borrowers.

26. Huber\White\sandwich estimators of the variance are utilized. Likewise, the regression is estimated (results not shown) to account for cluster effects among group members. However, the results do not change significantly.

data, the above interpretation gains credence by the fact that a negative coefficient appears in areas of the city that were built prior to 1960 and that are classified as urban (rather than suburban) by Statistics Canada.

Before making a final claim on the peer group effect, one must also consider that there may be unobservable characteristics associated with borrower default or with belonging to a peer group that would bias the results in Table 7, column 3. To this end, a variety of additional controls (typically unavailable in conventional datasets) are entered into the regression to account for individual-level heterogeneity and self-selection. This includes the individual's credit history, net worth, knowledge of computers, and self-employment training.[27] The results do not change appreciably. Lastly, it is possible that the peer group dummy is proxying for group-specific characteristics that are correlated to lower levels of default. To account for this, a random-effects probit model is also estimated in Table 7, column 4. Although one can reject the null hypothesis that the within-group variation is zero, the peer group dummy does not change significantly from the simple probit estimates in column 3.

5.2 Does belonging to a peer group reduce the size of borrower default?

Table 8 reports the estimation of equation (4) by ordinary least squares (OLS) and Tobit specification. For the full Tobit specification, the results are qualitatively similar to the simple probit estimation, despite the smaller sample limited to the Metropolitan Toronto region. Similar to the simple default estimation, single male borrowers with start-up businesses located outside the home tend to experience higher default amounts. However, for the full specification in column 4, which includes neighbourhood and background heterogeneity controls, the peer group dummy does not predict significantly lower default amounts, even when controlling for the loan size.

The results reported in Tables 7 and 8 therefore suggest that peer group borrowers tend to default less often than individual borrowers, but that, conditional on defaulting, lower default-loan amounts are not as strongly linked to peer group lending. Could it be the case, however, that safer, more risk-averse borrowers tend to prefer group loans (and the support that they would receive from fellow group members) over individual loans? And that, conversely, individual borrowers may be those entrepreneurs who know they have risky projects, and thus prefer to borrow alone, either to avoid having to bear the cost of social sanctions from their group members if they default, or because they cannot find a group that would tolerate their risky project?

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27. Also, measures of social capital, such as belonging to an organization or how well one knows one's neighbours, are entered into the regression. In all cases, the coefficients do not affect the peer group dummy (results available upon request).

5.3 Accounting for self-selection

5.3.1 Estimates of treatment effects

Of course, the problem of self-selection noted above may affect the estimate of belonging to a peer group, since safer borrowers may be sorting themselves into group loans. To isolate the incentive effects of group borrowing, a treatment-effects approach is first employed. Table 9 (columns 1 and 2) reports the marginal effects from the probit model and compares them with the estimates from a linear-probability model. The results are broadly similar with those in Table 7.

Column 3 in Table 9 estimates a linear-probability treatment-effects model to account for any potential self-selection. The decision to participate in a group loan program is identified using the borrower's age and the size of the business (first-stage results are not shown). Older borrowers tend to prefer group loans, and age is not correlated with the error term in the second stage (as confirmed by the Sargan statistic—the instruments cannot be rejected). Borrowers with larger businesses generally demand larger loans, which are available only under the individual loan program. Although age is strongly correlated with the type of loan choice, larger businesses are only weakly related to individual loans. The results, while broadly consistent with the probit marginal effects and OLS estimates in column 1, do differ in that the peer group dummy falls by 3 percentage points (17 per cent lower) and becomes statistically insignificant.[28] This latter effect is typical, however, of standard selection correction and instrumental variables approaches that rely heavily on first-stage identification, where the presence of weak instruments or small sample sizes (our case) can cause standard errors to inflate and significance levels to fall.

5.3.2 Matching-methods estimates

Apart from first-stage identification difficulties, the treatment-effects model described above assumes that program participation would affect participants and non-participants equally. As noted in section 4.2, if the respective distributions of borrower characteristics do not share common supports, then the treatment effect may be biased. To account for this potential bias, matching-method techniques are used to generate an analogous control group. First, a probit regression is estimated to generate the propensity score for the likelihood of a borrower selecting a group loan; the results are reported in Table 10.[29]

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28. Estimation of an instrumental variable's linear-probability model produces even weaker results, but in both cases identification is weak. The F-statistic on the variables excluded in the first stage is less than 10. This suggests a weak instrument problem (Staiger and Stock 1997).

29. 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. Also note that group borrowers are older, have lower incomes, and run home-based businesses. Interestingly, certain loan managers are more likely than others to grant group loans.

Figure 1 shows the distribution of the propensity score for group and individual borrowers for unmatched, matched without replacement, and matched with replacement samples. The kernel density estimates and the histograms clearly show that the distribution of the propensity score for group borrowers is heavily skewed to the right when compared with individual borrowers. To account for the heavy right tail, a simple trimming procedure is conducted. Following Ham, Li, and Reagan (2003), propensity scores that fall below/above a certain level are removed from the sample until a total of 5 per cent of the total sample is eliminated. The procedure is also conducted for trimming at the 10 per cent and 15 per cent levels, respectively. Figure 2 shows how trimming reduces a portion of the right tail for the distribution of propensity scores for group borrowers. The results of utilizing nearest-neighbour matching methods are reported in Table 11 for no trimming and for 5, 10, and 15 per cent trimming levels.[30] The results for the simple matching without replacement cohere with the standard probit results in Table 7, indicating that incentive effects, which lead to higher borrower effort, are an operative feature of the group lending program. For the simple dummy variable approach—columns 1 and 2—belonging to a peer group tends to reduce the likelihood of borrower default. Note that if self-selection is the most important factor driving the peer group effect, then when we control for it using matching estimates the coefficient for the peer group dummy should fall and at the limit approach zero. Estimation of the full specification in columns 3 and 4 leads to similar probit coefficients on our peer group dummy, although lack of precision in the non-replacement estimates (3) leads to a statistically insignificant result.

When replacements are used, however, and the sample is trimmed to ensure common supports, the effect of peer group membership increases, because trimming removes group borrowers whose propensity score is close to one (i.e., those borrowers who would not be able to qualify for an individual loan, or who prefer the peer group environment). This group of borrowers are typically poor credit risks, leading to a greater estimated peer group effect.

5.4 Robustness check I: comparing probit results across peer loan subgroups

Considering the nature of the groups included in the sample, the use of matching methods in Table 11 still may not capture the true sorting effect of 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. This will occur only if the borrowers know and/or trust each other well. If

30. Local linear regression and quadratic matching techniques may offer improvements over nearest-neighbour estimates, but the small sample size precludes use of these alternative matching estimators. However, the benefits of more sophisticated matching techniques are not always clear (Ham, Li, and Reagan 2003).

groups are made up of individuals who have little or no connection with each other, the peer group effect will be greatly weakened. The treatment and matching results may indicate that the sample of group borrowers includes groups that do not know and trust each other well. If group members know each other well, then the estimates of the peer group effect should be larger than when all groups are included. To account for this, groups are clustered by levels of group trust and the estimation results are reported across a range of specifications (rows 1 to 6) in Table 12.[31]

The results in column 1 show that when high-trust groups are excluded, the peer group effect is muted. On the other hand, the estimate of the effect of peer group membership becomes larger than the original pooled sample when only high-trust groups are included (column 2). This confirms that peer group lending is more effective when groups know and trust each other.

5.5 Robustness check II: comparing matching with "fine" and "coarse"

5.5.1 Balancing

The results from splitting the sample into high- and low-trust groups are checked utilizing matching methods. In Table 11, borrowers are matched solely by their propensity score, otherwise known as "coarse" matching. If we utilize a "finer matching" approach, as in Ham, Li, and Reagan (2003), then borrowers can be split into distinct groups, which in our case are those with high and low levels of trust. Once group borrowers are split, they are matched to their closest counterpart in the control group. The results are reported in Table 13. In both high- and low-trust cases, fine matching does not dissipate the negative probit estimate on peer loans, which suggests that the peer group effect associated with greater borrower effort is still present. Specifically, a comparison of column 4 in Tables 11 and 13 shows that the peer group effect is influenced by the level of group trust, such that coarse matching in Table 11 provides a middle-road estimate of the effect of peer group lending on borrower default, lying above and below low- and high-trust groups, respectively. Table 13, therefore, can be thought of as providing lower- and upper-bound estimates of the peer-group treatment effect.

In fact, by matching with low-trust group borrowers only (excluding high-trust borrowers), we mitigate the self-selection effect to the greatest degree, which allows us to identify the true impact of higher effort on loan default rates.[32]

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31. Group trust is measured by how well group members trust each other and whether they know their fellow group members prior to applying for a loan.
32. While the results are not significant for the full specification, this is due largely to the lack of precision, which is a consequence of utilizing the matching estimator.

6. Conclusion

Theoretical models of group lending and peer pressure drawn from the microfinance and personnel economics literature predict that peer monitoring will lead to more effective borrower-side sorting and higher borrower effort. Although these proximate effects are hard to measure, one should expect that, if operative, group borrowers would outperform individual borrowers in terms of repayment success. We have found evidence consistent with these theoretical claims; namely, that group lending outperforms conventional individual lending techniques. However, since the channels by which this effect occurs have been inferred rather than measured (e.g., we have no real data on actual effort levels, only effects that remain significant and sizable after controlling for self-selection), one must be slightly cautious about whether group lending works *as predicted* by the recent theoretical literature and as touted by practitioners. One should also acknowledge that the effectiveness of peer group lending can be mitigated by variables such as the size of the loan, the quality of the loan manager, levels of trust, and the enforcement of social norms either within the group or in the surrounding neighbourhood.

The evidence reported in this paper also raises several important future areas of research. First, although peer groups do appear to work in these two particular MFIs, can this result be generalized to the wider fields of microfinance and workplace teams? Second, how are group norms actually enforced? Is it the case that *all* borrowers exert greater effort in groups than on their own? If true, 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 trade-off could be insightful. It is clear that further theoretical and empirical work is necessary to resolve these questions.

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Table 1: Loan Terms, Characteristics, and Delinquency Rates

	All clients	Paid out* clients	Delinquent* clients	Group clients	Ind. clients
Loan size ($)	1639 (1000)	1319 (1000)	1716 (1000)	1031 (1000)	3954 (2700)
Loan term (months)	13.8 (12.0)	12.3 (12.0)	14.4 (12.0)	11.4 (12.0)	23.1 (18.0)
Loan payment ($/month)	112.6 (88.9)	105.0 (88.9)	114.3 (88.9)	94.7 (88.9)	220.5 (184.8)
Household income/ loan payment	15.9 (12.5)	17.0 (13.8)	13.6 (10.9)	16.7 (13.5)	11.8 (10.2)
Business revenue/ loan payment	26.0 (15.8)	26.1 (16.4)	30.0 (19.6)	25.3 (15.8)	30.5 (16.0)
Business profit/ loan payment	9.1 (6.2)	8.3 (6.4)	14.9 (7.2)	8.6 (6.4)	12.6 (5.3)
Default rate (%)	24.3			21.2	41.4

Notes: Household 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 out” refers to clients who successfully repaid their loans, and “Delinquent” refers to those borrowers who defaulted on their loans. Parentheses indicate median.

Table 2a: Demographic Characteristics

(All figures in percentage terms unless otherwise noted)	All clients	Paid out* clients	Delinquent* clients	Group clients	Ind. clients
Gender					
Male	47.6	43.4	56.6	46.2	53.4
Female	52.4	56.6	43.4	53.8	46.6
Ethnicity					
Caucasian	50.7	50.8	50.6	51.2	48.6
Europe/Arabic	1.9	2.6	0.0	2.0	1.2
African	34.8	30.4	43.9	32.8	43.2
East/South Asian	4.1	4.5	2.4	4.3	3.7
Hispanic	7.5	10.2	2.8	8.6	3.3
Other	1.0	1.4	0.4	1.2	0.0
Immigrant status					
Immigrant	38.5	41.7	33.5	41.9	24.5
Native-born	61.5	58.3	66.5	58.1	75.5
Neighbourhood					
Toronto	37.0	41.4	32.0	39.5	26.8
Scarborough	9.8	9.8	10.8	10.9	5.3
Etobicoke	5.6	5.9	6.8	6.4	2.9
North York	4.9	5.3	4.4	4.5	6.6
York	4.6	6.3	2.0	5.4	1.2
Mississauga	5.6	4.9	8.4	5.7	4.9
Markham	1.9	1.7	3.2	2.2	0.8
Pickering	2.9	3.0	1.6	2.9	2.9
Halifax-urban	14.2	11.2	16.4	10.9	27.6
Halifax-rural	13.5	10.3	14.8	11.6	21.4

*"Paid out" refers to clients who successfully repaid their loans, and "Delinquent" refers to those borrowers who defaulted on their loans.

Table 2b: Demographic Characteristics

(All figures in percentage terms unless otherwise noted)	All clients	Paid out* clients	Delinquent* Clients	Group clients	Ind. clients
Marital status					
Single	46.1	45.3	50.0	47.2	41.5
Married	39.3	40.2	32.0	36.6	50.2
Divorced	8.9	9.1	7.6	9.1	8.3
Other	5.7	5.4	10.4	7.2	0.0
Education					
Univ. degree	23.3	26.9	15.0	24.7	18.0
College degree	28.9	28.5	27.5	28.6	29.8
High school	39.1	37.0	45.6	37.3	46.0
Less than high school	8.7	7.6	11.9	9.4	6.2
Skills training in business activity	29.5	35.0	17.6	30.1	27.1
Self-employment training	40.4	40.1	43.8	41.0	38.4
Average age (years)	42.9	43.4	41.3	43.7	39.8
Average number of dependants	1.9	1.9	1.8	1.9	2.0

*"Paid out" refers to clients who successfully repaid their loans, and "Delinquent" refers to those borrowers who defaulted on their loans.

Table 3: Credit History

	All clients	Paid out* clients	Delinquent* clients	Group clients	Ind. clients
Sources of credit					
None	39.0	34.8	54.6	38.0	42.2
Bank	4.9	4.3	6.1	4.5	6.4
Credit cards	40.3	43.8	28.3	41.4	36.4
Family/friends/other	4.8	5.3	5.6	5.8	1.4
Multiple source	11.0	11.9	5.6	10.2	13.6
Credit statistics					
Limit ($)	7935 (2722)	7566 (3024)	5302 (435)	6443 (2400)	11017 (3093)
Balance ($)	5577 (1512)	5288 (1510)	4430 (636)	4631 (1310)	7544 (2020)
Net limit ($) (limit-balance)	2358 (62)	2266 (232)	872 (0)	1824 (62)	3488 (79)
Utilization rate	0.87 (0.98)	0.86 (0.93)	0.97 (1.00)	0.85 (0.98)	0.93 (0.96)
Credit payment ($/month)	235 (85)	229 (81)	200 (53)	195 (70)	368 (172)
Credit payment/ Household income + Business revenue	0.07 (0.02)	0.06 (0.02)	0.06 (0.02)	0.06 (0.02)	0.08 (0.03)
Credit history (ratio of borrowers reporting a credit incident)					
Credit history	0.86	0.87	0.77	0.84	0.89
R9	0.40	0.34	0.45	0.39	0.40
Collections	0.13	0.09	0.22	0.11	0.17
Bankruptcies	0.10	0.10	0.10	0.11	0.08

*"Paid out" refers to clients who successfully repaid their loans, and "Delinquent" refers to those borrowers who defaulted on their loans. Parentheses indicate median.

Table 4: Household Characteristics

(All figures in percentage terms unless otherwise noted)	All clients	Paid out* clients	Delinquent* clients	Group clients	Ind. clients
Monthly household income	1510 (1200)	1567 (1250)	1325 (1000)	1451 (1200)	1728 (1450)
Household assets	23466 (9500)	22680 (10000)	18607 (7000)	20009 (8000)	34794 (12750)
Household liabilities	12507 (2500)	12006 (2750)	9208 (1500)	10790 (2500)	17967 (2700)
Net worth	10930 (4620)	10586 (4600)	9506 (4500)	9138 (4234)	16959 (7100)
Sources of income					
Wages or salary	49.1	50.9	51.2	50.5	45.7
Govt. assist.	26.6	30.3	19.5	31.4	14.9
Interest, etc.	2.6	4.1	0.0	3.4	0.5
Private pension	0.7	1.0	0.0	1.0	0.0
Employment status					
Full time	35.7	32.4	41.9	32.8	42.7
Part time	12.4	16.0	8.5	15.7	4.4
Both	0.4	0.5	0.0	0.6	0.0
Not working	51.5	51.2	49.6	50.9	52.9
Importance of business income					
Only source	24.5	23.7	33.3	24.5	25.0
Major source	15.0	15.9	6.1	14.8	17.8
Supplement	60.5	60.3	60.6	60.8	57.1

*"Paid out" refers to clients who successfully repaid their loans, and "Delinquent" refers to those borrowers who defaulted on their loans. Parentheses indicate median.

Table 5: Business Characteristics

(All figures in percentage terms unless otherwise noted)	All clients	Paid out* clients	Delinquent* clients	Group clients	Ind. clients
Monthly revenues	3239 (1700)	2878 (1572)	3753 (2000)	2579 (1500)	5889 (2880)
Monthly costs	2140 (881)	1924 (817)	2261 (900)	1714 (786)	3839 (1725)
Monthly profits	1110 (600)	959 (600)	1525 (601)	856 (575)	2103 (968)
Ownership type					
Sole proprietorship	84.5	85.5	85.2	85.9	79.6
Partnership	7.9	7.0	7.7	7.8	8.2
Incorporated	6.8	6.8	5.3	5.4	11.8
Other	0.8	0.7	1.9	0.9	0.5
Start-up business	37.6	34.7	44.0	37.0	40.0
Business location					
Home	75.0	76.1	69.5	76.3	69.8
Store/shop/other	25.0	23.9	30.5	23.7	30.2

*"Paid out" refers to clients who successfully repaid their loans, and "Delinquent" refers to those borrowers who defaulted on their loans. Parentheses indicate median.

Table 6: Survey Data of Group Characteristics

(All figures in percentage terms unless otherwise noted)	All clients	Paid out* clients	Delinquent* clients	Group clients	Ind. clients
Proportion of group known well before Calmeadow					
Mean	0.55	0.57	0.42	0.55	na
Median	0.50	0.60	0.25	0.50	na
How much trust existed within group					
A great deal	52.5	53.3	40.5	54.4	na
Some	31.3	31.4	33.3	31.2	na
Little	10.0	9.8	14.3	10.3	na
None	3.0	3.2	2.4	2.9	na
Don't know	3.3	2.2	9.5	1.2	na
Are you a member of team, club, association, or organization					
Yes	48.6	51.3	30.3	48.6	48.4
No	51.4	48.7	69.7	51.4	51.6
Motivations for repayment: Don't want to let group down					
Extremely important	79.2	81.1	64.3	81.5	na
Important	15.1	12.8	33.3	13.7	na
Somewhat important	3.6	4.2	0.0	3.6	na
Not important	2.2	1.9	2.4	1.2	na

*"Paid out" refers to clients who successfully repaid their loans, and "Delinquent" refers to those borrowers who defaulted on their loans.

Table 7: Probit Estimates of the Effect of Peer Group Lending on the Probability of Default (standard errors in parentheses)

	Peer group dummy only (1)	Household, demographic only (2)	Household, demographic, business, institutional, neighbourhood effects (3)	Household, demographic, business, institutional, neighbourhood, random effects (4)
Peer loan	-0.5820*	-0.6515*	-0.5595*	-0.6605*
	(0.1099)	(0.1325)	(0.2161)	(0.2892)
Household income [High income excluded]				
None		0.0364	-0.0059	0.0130
		(0.1754)	(0.2056)	(0.2439)
Low		0.2157	0.3193	0.3552**
		(0.1420)	(0.1631)	(0.1909)
Middle		-0.0175	0.0574	0.0665
		(0.1546)	(0.1687)	(0.2042)
[Married]				
Not married		0.2361*	0.3342*	0.3968*
		(0.1134)	(0.1316)	(0.1600)
Male		0.2638*	0.1814	0.1585
		(0.1053)	(0.1174)	(0.1486)
Immigrant		-0.1034	0.0415	0.0153
		(0.1425)	(0.1681)	(0.2040)
Ethnicity [Latin/South American excluded]				
Canadian		0.4924**	0.3386*	0.2920
		(0.2784)	(0.2968)	(0.3540)
European/M. East		0.2144	0.2225	0.2046
		(0.3454)	(0.3802)	(0.4476)
African-Canadian		0.8156*	0.7754*	0.8382*
		(0.2539)	(0.2678)	(0.3230)
[<high school excluded]				
University		-0.3447**	-0.2989	-0.3342
		(0.2094)	(0.2511)	(0.2925)

(continued)

Table 7: Probit Estimates of the Effect of Peer Group Lending on the Probability of Default (standard errors in parentheses) (continued)

	Peer group dummy only	Household, demographic only	Household, demographic, business, institutional, neighbourhood effects	Household, demographic, business, institutional, neighbourhood, random effects
	(1)	(2)	(3)	(4)
College		-0.0819	0.0840	0.1263
		(0.1941)	(0.2249)	(0.2720)
High school		-0.0388	-0.0008	0.0441
		(0.1826)	(0.2170)	(0.2582)
Technical training		-0.4387*	-0.3903*	-0.4739*
		(0.1201)	(0.1367)	(0.1626)
Source of outside credit			-0.3376*	-0.3680*
			(0.1220)	(0.1460)
Start-up			0.2586*	0.3327*
			(0.1207)	(0.1529)
Home-based business			-0.3466*	-0.4429*
			(0.1290)	(0.1631)
Loan size			0.0616**	0.0746
			(0.0344)	(0.0464)
Ln profits			-0.0186	-0.0272
			(0.0244)	(0.0309)
Institutional effects				
Manager 1			0.4971	0.5668
			(0.4011)	(0.4546)
Manager 2			-0.2344	-0.2501
			(0.3042)	(0.4208)
Manager 3			0.3337	0.3773
			(0.2058)	(0.2711)
Manager 4			-0.3601	-0.4270
			(0.2372)	(0.3042)
Manager 5			-0.2856	-0.3307
			(0.2538)	(0.3388)
[Mississauga excluded]				
Toronto			-0.5413*	-0.6158*
			(0.1932)	(0.2356)
Scarborough			-0.5423*	-0.6406**
			(0.2603)	(0.3141)

(continued)

Table 7: Probit Estimates of the Effect of Peer Group Lending on the Probability of Default (standard errors in parentheses) (concluded)

	Peer group dummy only (1)	Household, demographic only (2)	Household, demographic, business, institutional, neighbourhood effects (3)	Household, demographic, business, institutional, neighbourhood, random effects (4)
Etobicoke			-0.1565 (0.2792)	-0.0670 (0.3380)
North York			-0.8559* (0.3590)	-0.9852* (0.4746)
York			-1.0599* (0.3215)	-1.1308* (0.4360)
Halifax			0.0993 (0.1888)	0.1131 (0.2456)
Constant	-0.2183* (0.0994)	-0.8616* (0.3402)	-0.4453 (0.4765)	-0.4203 (0.5895)
N	1064	808	702	702
LR chi^2	28.03	83.12	109.24	75.31*
Pseudo R^2	0.0235	0.1142	0.1746	
ρ				0.3028
H_0: ρ=0 ($Chi^2(1)$)				11.35*

*Indicates significance at the 5 per cent level, **indicates significance at the 10 per cent level.

Table 8: Tobit Estimates of the Effect of Peer Group Lending on Amount of Loan Written Off (standard errors in parentheses)

	OLS household, demographic only (1)	OLS household, demographic, business, institutional, neighbourhood effects (2)	Tobit household, demographic only (3)	Tobit household, demographic, business, institutional, neighbourhood effects (4)
Peer loan	-516.25*	70.51	-1094.89*	-161.86
	(240.56)	(408.69)	(565.31)	(897.92)
Household income [High income excluded]				
None	-76.29	-48.50	95.35	324.60
	(113.41)	(101.57)	(855.95)	(847.61)
Low	-55.90	-14.51	179.85	420.80
	(86.12)	(83.55)	(536.50)	(537.64)
Middle	73.22	153.86	416.65	857.98
	(130.29)	(147.60)	(557.57)	(549.21)
[Married]				
Not married	143.53	224.72*	1056.29*	1421.57*
	(92.80)	(91.27)	(474.00)	(486.68)
Male	202.41*	151.34*	1533.00*	932.99*
	(98.93)	(69.54)	(431.82)	(438.04)
Immigrant	46.94	76.02	-50.75	23.68
	(112.71)	(115.00)	(540.25)	(505.20)
Ethnicity [Latin/South American excluded]				
Canadian	138.58	163.20	939.50	702.03
	(122.39)	(150.06)	(880.58)	(870.17)
European/M. East	-60.44	-30.70	-426.70	-50.52
	(79.82)	(100.14)	(1075.44)	(1099.92)
African-Canadian	51.39	134.08	1068.67	1273.22
	(76.74)	(80.36)	(754.97)	(754.16)
[< high school excluded]				
University	-58.59	-75.08	-567.78	-665.96
	(117.15)	(148.46)	(826.04)	(830.69)
College	67.67	138.29	287.29	584.35
	(138.50)	(180.00)	(758.26)	(756.80)
High school	-102.68	-47.35	-648.25	-382.00
	(95.92)	(126.06)	(757.50)	(765.65)

(continued)

Table 8: Tobit Estimates of the Effect of Peer Group Lending on Amount of Loan Written Off (standard errors in parentheses) (continued)

	OLS household, demographic only (1)	OLS household, demographic, business, institutional, neighbourhood effects (2)	Tobit household, demographic only (3)	Tobit household, demographic, business, institutional, neighbourhood effects (4)
Technical training		2.06		-884.45*
		(77.60)		(447.77)
Source of outside credit		-146.34		-900.22*
		(101.91)		(405.38)
Startup		134.23		906.53*
		(107.23)		(428.23)
Home-based business		-68.33		-936.93*
		(78.11)		(478.40)
Loan size		149.99		329.70*
		(115.77)		(114.22)
Ln profits		7.76		3.89
		(15.15)		(87.78)
Institutional effects				
Manager 1		258.69		1209.42
		(207.24)		(1122.29)
Manager 2		-85.45		-659.69
		(103.35)		(925.45)
Manager 3		-0.26		185.46
		(93.40)		(632.49)
Manager 4		-295.80**		-2099.67*
		(159.14)		(765.12)
Neighbourhood				
[Mississauga excluded]				
Toronto		-38.42		-1043.27**
		(113.38)		(611.42)
Scarborough		23.06		-582.86
		(141.06)		(748.26)
Etobicoke		13.83		-252.75
		(112.44)		(802.65)
North York		-89.51		-1456.77
		(295.00)		(1052.58)

(continued)

Table 8: Tobit Estimates of the Effect of Peer Group Lending on Amount of Loan Written Off (standard errors in parentheses) (concluded)

	OLS household, demographic only (1)	OLS household, demographic, business, institutional, neighbourhood effects (2)	Tobit household, demographic only (3)	Tobit household, demographic, business, institutional, neighbourhood effects (4)
York		-9.25		-1317.23
		(121.38)		(954.25)
Constant	429.83	-387.88	-4351.67*	-3842.85*
	(234.06)	(587.47)	(1390.76)	(1770.68)
N	633	567	633	567
F	0.89	0.93		
R^2	0.0607	0.1491		
LR chi^2			42.98	86.68
Pseudo R^2			0.0206	0.0471

*Indicates significance at the 5 per cent level, **indicates significance at the 10 per cent level

Table 9: Treatment-Effects Estimates of the Effect of Peer Group Lending on the Probability of Default (standard errors in parentheses)

	Probit, marginal effects	Linear-probability OLS	Linear-probability treatment effects
	(1)	(2)	(3)
Peer loan	-0.1668*	-0.1553*	-0.1370
	(0.0733)	(0.0659)	(0.1223)
Household income [High income excluded]			
None	-0.0015	-0.0075	-0.0074
	(0.0528)	(0.0533)	(0.0511)
Low	0.0860*	0.0802*	0.0802*
	(0.0454)	(0.0396)	(0.0389)
Middle	0.0150	0.0113	0.0113
	(0.0447)	(0.0392)	(0.0407)
[Married]			
Not married	0.0837*	0.0786*	0.0786*
	(0.0320)	(0.0324)	(0.0323)
Male	0.0472	0.0440	0.0441
	(0.0306)	(0.0305)	(0.0304)
Immigrant	0.0107	0.0052	0.0049
	(0.0436)	(0.0456)	(0.0427)
Ethnicity [Latin/South American excluded]			
Canadian	0.0877	0.0620	0.0620
	(0.0766)	(0.0555)	(0.0628)
European/M. East	0.0625	0.0540	0.0542
	(0.1153)	(0.0577)	(0.0743)
African-Canadian	0.2190*	0.1755*	0.1754*
	(0.0797)	(0.0447)	(0.0549)
[< high school excluded]			
University	-0.0717	-0.0650	-0.0644
	(0.0558)	(0.0691)	(0.0618)
College	0.0221	0.0155	0.0162
	(0.0600)	(0.0675)	(0.0595)
High school	-0.0002	-0.0015	-0.0011
	(0.0560)	(0.0648)	(0.0570)
Technical training	-0.0956*	-0.0892*	-0.0894*
	(0.0315)	(0.0312)	(0.0318)

(continued)

Table 9: Treatment-Effects Estimates of the Effect of Peer Group Lending on the Probability of Default (standard errors in parentheses) (continued)

	Probit, marginal effects	Linear-probability OLS	Linear-probability treatment effects
	(1)	(2)	(3)
Source of outside credit	-0.0906*	-0.0913*	-0.0910*
	(0.0338)	(0.0332)	(0.0309)
Startup	0.0691*	0.0644*	0.0645*
	(0.0336)	(0.0324)	(0.0315)
Home-based business	-0.0954*	-0.0848*	-0.0857*
	(0.0376)	(0.0355)	(0.0343)
Loan size	0.0159**	0.0185	0.0187**
	(0.0089)	(0.0114)	(0.0104)
Ln profits	-0.0048	-0.0030	-0.0027
	(0.0063)	(0.0063)	(0.0066)
Institutional effects			
Manager 1	0.1546	0.1051	0.1051
	(0.1437)	(0.1139)	(0.0963)
Manager 2	-0.0547	-0.0233	-0.0237
	(0.0635)	(0.0629)	(0.0707)
Manager 3	0.0893	0.0857	0.0856
	(0.0566)	(0.0475)	(0.0481)
Manager 4	-0.0825	-0.0935**	-0.0944**
	(0.0477)	(0.0543)	(0.0552)
Manager 5	-0.0656	-0.0363	-0.0357
	(0.0512)	(0.0794)	(0.0722)
Neighbourhood effects			
[Mississauga excluded]			
Toronto	-0.1315*	-0.1320*	-0.1317*
	(0.0439)	(0.0494)	(0.0475)
Scarborough	-0.1108	-0.1444*	-0.1439*
	(0.0402)	(0.0715)	(0.0665)
Etobicoke	-0.0378	-0.0070	-0.0067
	(0.0628)	(0.0825)	(0.0720)
North York	-0.1441*	-0.1972*	-0.1969**
	(0.0346)	(0.0794)	(0.0883)
York	-0.1656*	-0.2062*	-0.2059*
	(0.0262)	(0.0607)	(0.0729)

(continued)

Table 9: Treatment-Effects Estimates of the Effect of Peer Group Lending on the Probability of Default (standard errors in parentheses) (concluded)

	Probit, marginal effects	Linear-probability OLS	Linear-probability treatment effects
	(1)	(2)	(3)
Halifax	0.0265	0.0295	0.0295
	(0.0519)	(0.0571)	(0.0529)
Constant		0.3539*	0.3363*
		(0.1253)	(0.1572)
N	702	702	702
Wald chi^2	109.24		121.11
Pseudo R^2	0.1746		
F		4.94	
R^2		0.1718	

*Indicates significance at the 5 per cent level, **indicates significance at the 10 per cent level

Table 10: Probit Estimates of the Probability of Entering a Peer-Group Loan Program (standard errors in parentheses)

	Basic specification (1)	Basic specification age (2)	Basic specification revenue (3)	Basic specification age and revenue (4)
Household income [High income excluded]				
None	0.5733*	0.4628*	0.5862*	0.4777*
	(0.2155)	(0.2219)	(0.2155)	(0.2220)
Low	0.5349*	0.4860*	0.5316*	0.4840*
	(0.1571)	(0.1599)	(0.1578)	(0.1612)
Middle	0.3184**	0.2724**	0.3024**	0.2562
	(0.1607)	(0.1619)	(0.1587)	(0.1607)
[Married]				
Not married	0.1705	0.1885	0.1724	0.1904
	(0.1276)	(0.1294)	(0.1274)	(0.1291)
Male	-0.0987	-0.0725	-0.0980	-0.0724
	(0.1255)	(0.1272)	(0.1257)	(0.1273)
Immigrant	0.2233	0.1612	0.2212	0.1585
	(0.1666)	(0.1710)	(0.1664)	(0.1708)
Ethnicity [Latin/South American excluded]				
Canadian	-0.2797	-0.3445	-0.2658	-0.3274
	(0.2792)	(0.2831)	(0.2818)	(0.2857)
European/M. East	-0.0408	0.0623	-0.0459	0.0561
	(0.3085)	(0.3057)	(0.3128)	(0.3087)
African-Canadian	-0.3549	-0.4037	-0.3420	-0.3887
	(0.2575)	(0.2588)	(0.2601)	(0.2611)
[< high school excluded]				
University	-0.3633	-0.2807	-0.3336	-0.2484
	(0.2719)	(0.2798)	(0.2740)	(0.2813)
College	-0.2581	-0.1427	-0.2343	-0.1165
	(0.2622)	(0.2691)	(0.2653)	(0.2714)
High school	-0.2198	-0.2057	-0.2070	-0.1918
	(0.2550)	(0.2644)	(0.2566)	(0.2656)
Technical training	-0.1369	-0.1668	-0.1486	-0.1822
	(0.1303)	(0.1317)	(0.1300)	(0.1314)
Source of outside credit	0.1288	0.1310	0.1432	0.1494
	(0.1244)	(0.1263)	(0.1236)	(0.1252)

(continued)

Table 10: Probit Estimates of the Probability of Entering a Peer-Group Loan Program (standard errors in parentheses) (continued)

	Basic specification (1)	Basic specification age (2)	Basic specification revenue (3)	Basic specification age and revenue (4)
Start-up	0.1987 (0.1261)	0.1839 (0.1261)	0.1964 (0.1269)	0.1808 (0.1268)
Home-based business	0.3201* (0.1324)	0.2984* (0.1345)	0.2836* (0.1348)	0.2593* (0.1364)
Institutional effects				
Manager 1	0.1077 (0.4991)	-0.0462 (0.5217)	0.1392 (0.4918)	-0.0156 (0.5147)
Manager 2	-0.5528* (0.1982)	-0.5436* (0.1968)	-0.5390* (0.1959)	-0.5305* (0.1948)
Manager 3	-1.5124* (0.2047)	-1.7813* (0.2219)	-1.4941* (0.2042)	-1.7652* (0.2221)
Manager 4	-2.9156* (0.2710)	-2.8617* (0.2702)	-2.9102* (0.2731)	-2.8552* (0.2729)
Neighbourhood effects [Mississauga excluded]				
Toronto	-0.0310 (0.1763)	-0.0217 (0.1790)	-0.0175 (0.1754)	-0.0045 (0.1778)
Scarborough	-0.0402 (0.2441)	-0.0118 (0.2450)	-0.0362 (0.2438)	-0.0007 (0.2454)
Etobicoke	0.3260 (0.3256)	0.3361 (0.3224)	0.3220 (0.3277)	0.3317 (0.3213)
North York	-0.7811* (0.2933)	-0.8296* (0.3116)	-0.7576* (0.2919)	-0.7998* (0.3104)
York	0.1653 (0.3572)	0.1957 (0.3538)	0.1786 (0.3545)	0.2147 (0.3506)
Halifax	-0.0921 (0.2206)	-0.0571 (0.2180)	-0.1213 (0.2188)	-0.0882 (0.2166)
[Age<30 excluded]				
Age 31-40		0.1323 (0.1928)		0.1368 (0.1942)
Age 41-50		0.1020 (0.1895)		0.1046 (0.1906)
Age 51-60		0.4877* (0.2370)		0.5010* (0.2353)
Age 61+		1.1854* (0.3227)		1.1882* (0.3201)

(continued)

Table 10: Probit Estimates of the Probability of Entering a Peer-Group Loan Program (standard errors in parentheses) (concluded)

	Basic specification (1)	Basic specification age (2)	Basic specification revenue (3)	Basic specification age and revenue (4)
Ln revenues			-0.0361	-0.0390
			(0.0297)	(0.0290)
Constant	1.7319*	1.6053*	1.9602*	1.8433*
	(0.4444)	(0.4799)	(0.4939)	(0.5248)
N	894	894	894	894
Wald chi^2	263.63	273.95	262.73	272.00
Pseudo R^2	0.4096	0.4343	0.4115	0.4365

*Indicates significance at the 5 per cent level, **indicates significance at the 10 per cent level

Table 11: Matching Estimates of the Effect of Peer Group Lending on the Probability of Default (standard errors in parentheses)

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

* Indicates significance at the 5 per cent level, **indicates significance at the 10 per cent level. Bootstrapped standard errors, 100 reps. Cell entries represent probit results comparable with those found in Tables 7 and 13.

Table 12: Robustness Check I: the Effect of Peer Group Lending on the Probability of Default Within Group Trust and Loan Size Subgroups (standard errors in parentheses)

	High-trust groups excluded	Low-trust groups excluded	Loan size <=$1000	Loan size <=$2000
	Peer loan coefficients			
1. Probit - peer group dummy only	-0.4709* (0.1121)	-0.5753* (0.1183)	-0.9935* (0.2188)	-0.7649* (0.1552)
2. Probit - full specification	-0.4348* (0.2208)	-0.6251* (0.2283)	-0.8874* (0.3463)	-0.7357* (0.2612)
3. Probit - full specification, RE	-0.5160** (0.2960)	-0.7161* (0.3114)	-1.1100* (0.4810)	-0.7159* (0.3695)
4. Probit - full specification marginal probability	-0.1396* (0.0761)	-0.1885* (0.0754)	-0.2773* (0.1329)	-0.1843* (0.0940)
5. OLS linear probability	-0.1224** (0.0684)	-0.1690* (0.0684)	-0.2821* (0.1224)	-0.1899* (0.0832)
6. Treatment effects linear probability (ML)	-0.0605 (0.1309)	-0.2054 (0.1321)	-0.2372 (0.2180)	-0.1824 (0.1882)

* Indicates significance at the 5 per cent level, **indicates significance at the 10 per cent level

Table 13: Robustness Check II: "Fine" Matching Estimates of the Effect of Peer Group Lending on the Probability of Default (standard errors in parentheses)

	Peer group dummy only		Full specification	
	w/o replacement (1)	with replacement (2)	w/o replacement (3)	with replacement (4)
High-trust group borrowers excluded				
No trimming	-0.6643*	-0.9430*	-0.3235	-0.1846
	(0.1830)	(0.0816)	(0.3136)	(0.1335)
5% trimming	-0.6871*	-1.0563*	-0.3991	-0.3447*
	(0.1705)	(0.0829)	(0.3408)	(0.1490)
10% trimming	-0.7571*	-1.0816*	-0.4478	-0.3478*
	(0.1970)	(0.1000)	(0.3746)	(0.1689)
15% trimming	-0.7484*	-1.0970*	-0.4299	-0.3534*
	(0.2040)	(0.0928)	(0.3770)	(0.1835)
Low-trust group borrowers excluded				
No trimming	-0.7255*	-0.9385*	-0.6690*	-0.6182*
	(0.1886)	(0.1103)	(0.3050)	(0.2150)
5% trimming	-0.7746*	-1.1419*	-0.7590**	-0.8387*
	(0.2190)	(0.1069)	(0.3948)	(0.2324)
10% trimming	-0.7328*	-1.1224*	-0.7197*	-0.8015*
	(0.1936)	(0.1032)	(0.3400)	(0.2168)
15% trimming	-0.6731*	-1.0862*	-0.7000**	-0.7643*
	(0.2106)	(0.1238)	(0.3882)	(0.2382)

* Indicates significance at the 5 per cent level, **indicates significance at the 10 per cent level. Bootstrapped standard errors, 100 reps. Cell entries represent probit results comparable with those found in Tables 7 and 11.

Figure 1: Matching Results, Distribution of the Propensity Score

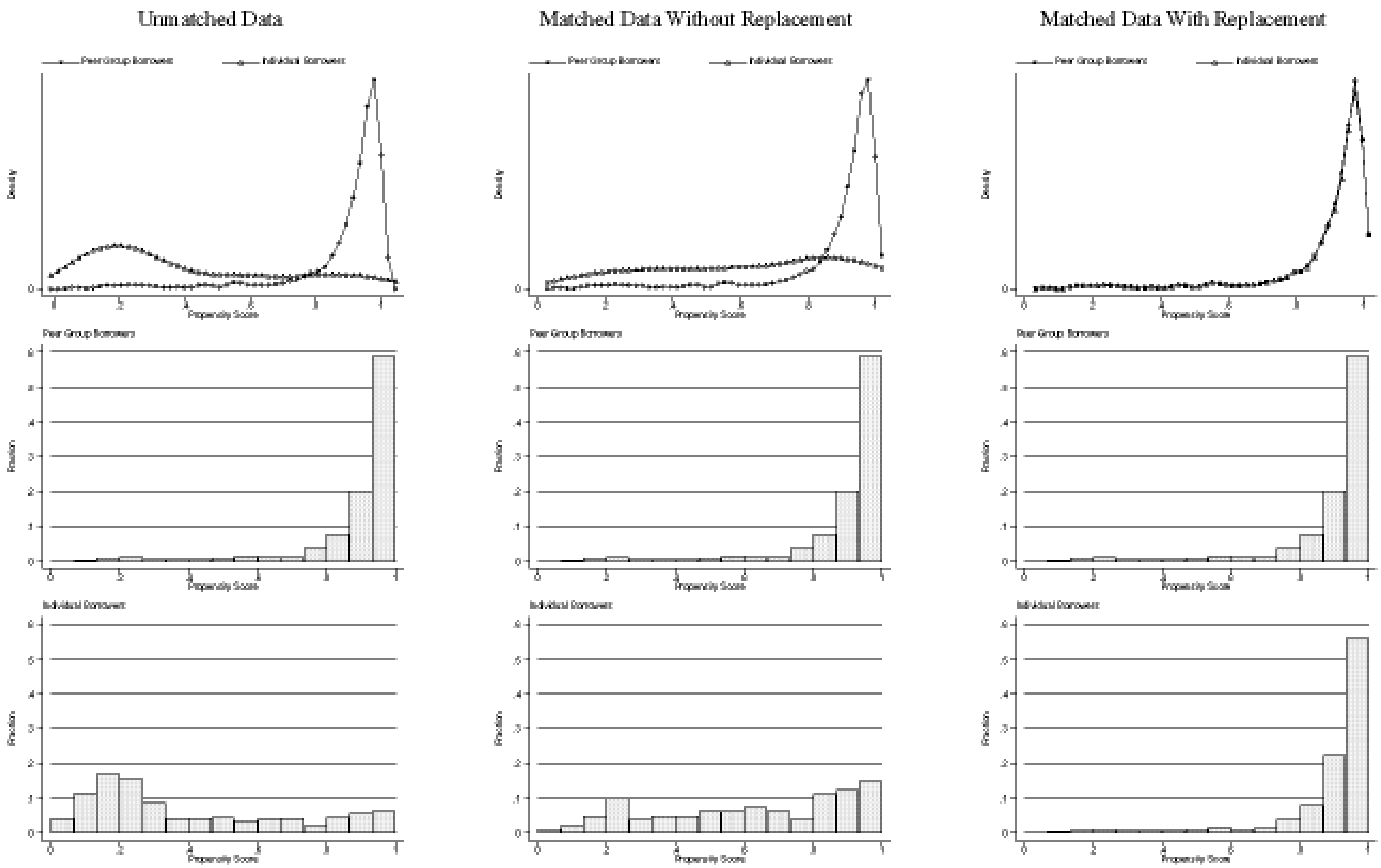


Figure 2: Trimmed Matching Results, Distribution of the Propensity Score

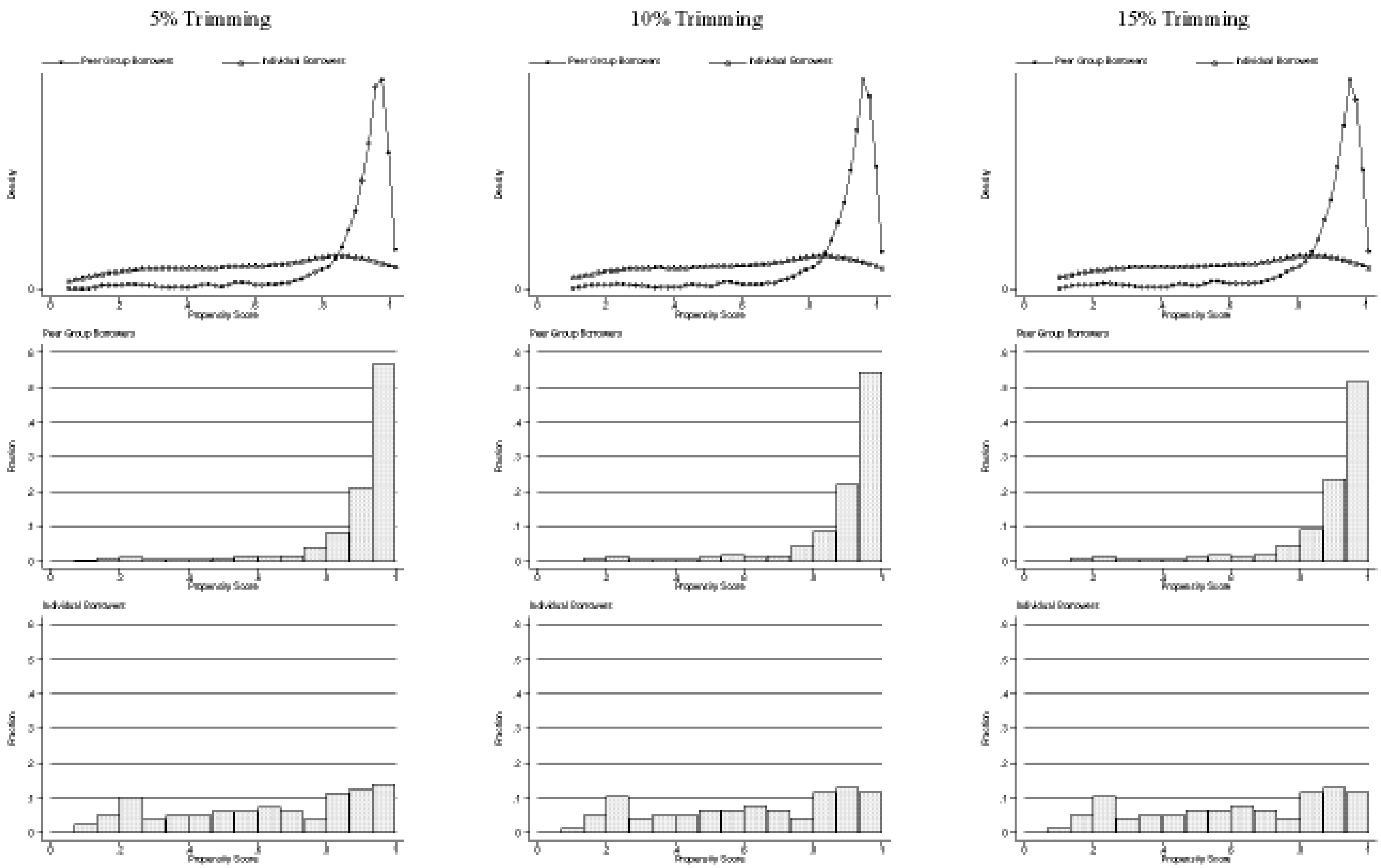


Figure 3: Trimmed Matching Results Without Replacement (High-Trust Groups Excluded), Distribution of the Propensity Score

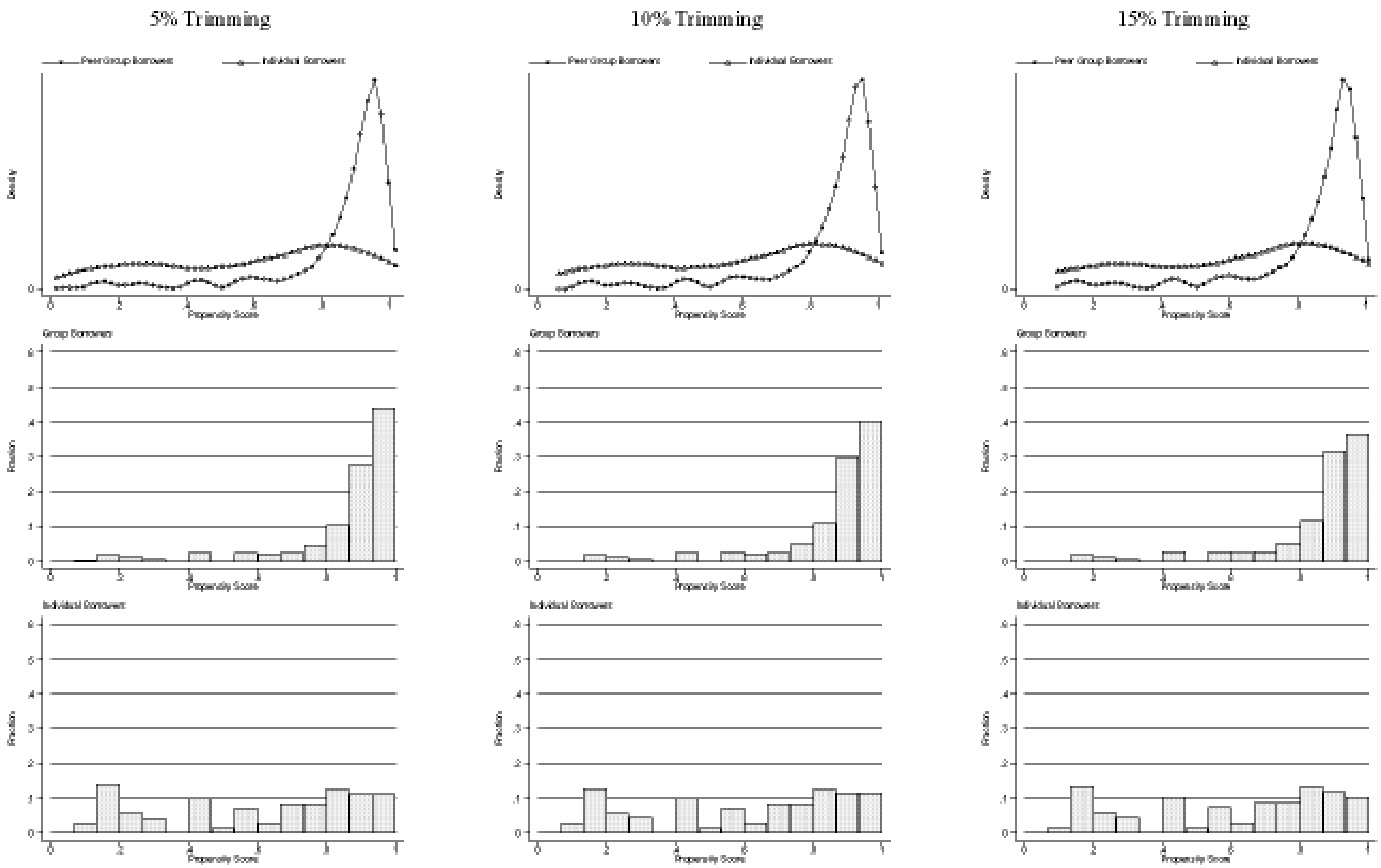
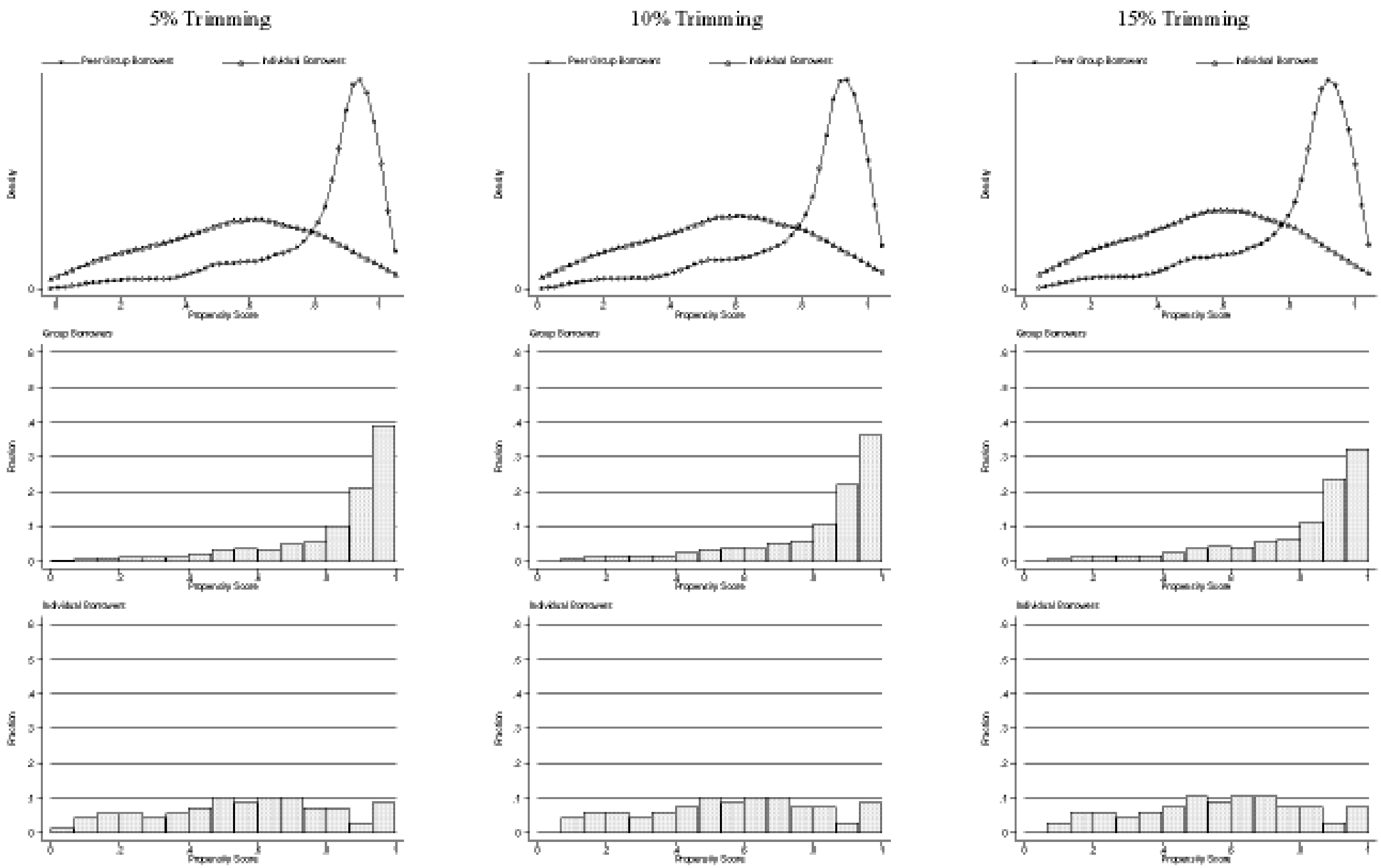


Figure 4: Trimmed Matching Results Without Replacement (Low-Trust Groups Excluded), Distribution of the Propensity Score



Appendix A: A Note on Calmeadow’s Lending Mechanism

Calmeadow offers two types of loans: group and individual. Group loans range in size from $500 to $5,000, with $1,000 being the typical loan size for first-time borrowers. The loan term is typically 12 months and early repayment is an option, with no penalty. The group lending format has the following features. Any group of four to seven borrowers can apply for a loan from Calmeadow, and borrowers must form their group before applying for a loan.[1] For the loan application, group borrowers must provide personal information, references, and business and demographic information on the loan application form. This information must 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 occurs once group members have approved each other’s applications. Calmeadow loan managers then assess the group’s application; collateral is not required, but credit checks are performed. 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.[2]

Calmeadow also offers individual loans that range in size from $1,000 to $15,000 over longer terms (up to 60 months), and to which anyone can apply.[3] The screening process is more rigorous: borrowers must have an existing business over 12 months old, be registered, provide a more sophisticated business plan, and occasionally provide collateral (usually, the fixed asset purchased with loan funds).[4] Consequently, Calmeadow views individual borrowers as being “better” clients in terms of loan application requirements. The criteria by which borrowers are sorted into 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.

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1. Despite being in a peer-group loan program, all borrowers operate their own individual businesses.
2. 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 behaviour will result in their fellow group members’ inability to access future loans.
3. Unlike many MFIs, Calmeadow does not means test its clients; any individual, regardless of their socio-economic well-being (unlike the Grameen Bank, for instance, which prevents wealthier individuals from applying), can apply for a loan.
4. The criterion regarding the age of a business is occasionally relaxed if the individual has self-employment training.

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 also substantial individual costs to non-repayment (that are independent of the joint liability costs), because defaulting results in a serious deterioration of that individual's credit history and in the submission of the loan claim to a collection agency. This "R9" on the borrower's credit history will make them unable to access any formal credit far into the future.

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