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Intermediation in Peer-to-Peer Markets: Evidence from Auctions for Personal Loans

Thilo Klein

Zentrum für Europäische
Wirtschaftsforschung GmbH

Centre for European
Economic Research

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Abstract

I examine the role of intermediaries on the world's largest peer-to-peer online lending platform. This marketplace as well as other recently opened lending websites allow people to auction microcredit over the internet and are in line with the disintermediation in financial transactions through the power of enabling technologies. On the online market, the screening of potential borrowers and the monitoring of loan repayment can be delegated to designated group leaders. I find that, despite superior private information, these financial intermediaries perform worse than the average lender with respect to borrower selection. I attribute this to deliberately sending wrong signals. Bivariate probit estimates of the effect of group membership on loan default indicate positive self selection into group loans. That is borrowers with worse observed and unobserved characteristics select into this contract form. I provide evidence that this is due to a missleading group reputation system that is driven by a short term incentive design, which was introduced by the platform to expand the market and has been discontinued. I further find that, after controlling for this group growth driven selection effect, group affiliation per se significantly reduces the probability of loan default.

JEL-Classification: C57, D02, D47, D82, G21, O16

Keywords: peer-to-peer, finance, market design, matching, auctions

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†Centre for European Economic Research (ZEW), Mannheim, Germany. Email: thilo.klein@zew.de

1 Introduction

How much would you lend to a person you have never met before? Assume it is online and there is no collateral to secure a defaulting loan. If your answer is something like "maybe one Dollar" you are probably in good company.

So how can we explain the fact that there are currently \$162 Millions of current loans on one online lending platform alone? These loans are funded online, peer-to-peer, in principle without people knowing each other and uncollateralized, meaning that the lender has to bear the full risk in case of loan default. Furthermore lenders are not solely seeing this as an act of charity, but as a promising investment. They create portfolio plans and discuss their investment strategies on various online forums.

The motivations of lending online peer to peer are manifold. Besides cutting out banks as the middlemen and thereby reducing the spread between borrower and lender rate (Chircu and Kauffman, 2000), one major driver of the concept's recent success is the rapid growth of social funds and ethic banking (Heng et al., 2007). Lenders may just feel comfortable with the idea of helping peers to realize their ideas, businesses or passions. Studying alternatives to traditional lending is also important from the borrower's perspective. There is economic evidence that the poor in the United States have an unmet demand for finance. Zeldes (1989) finds that poor households are borrowing constrained. They would like to borrow more money at existing rates than they can. Evans and Jovanovic (1989), even after controlling for possible correlation between entrepreneurial ability and wealth, find that a lack of wealth affects the poor's ability to become self-employed. Bond and Townsend (1996), who report on the results of a survey of financial activity in a low-income neighborhood in Chicago, find that bank loans are not an important source of finance for start-ups. Only 11.5 percent of business owners in their sample financed their start-up with a bank loan. Furthermore, 50 percent of the respondents financed their start-up entirely out of their own funds.

The online marketplace at hand, as one of these alternatives to traditional lending, is an online auction website where individuals can buy loans and request to borrow money. It is also often referred to as the eBay for loans. The lending process is managed by a reverse dutch auction, assembling bids with the lowest interest rates in order to fund the loan. Borrowers first write their listing and set the maximum interest rate they wish to pay. Lenders can then bid on specific loans by committing a portion of the principal and setting the minimum interest rate they wish to receive on a particular loan.

To reduce scam on the platform, the online market verifies selected borrowers' identity before funding loans and manages loan repayment. All loans are made by WebBank, a Utah-chartered Industrial Bank and sold to winning bidders registered as lenders. Lenders are therefore loan purchasers. Their unsecured loans are fully amortized over three years, with no pre-payment penalty. The company generates revenue by collecting a one-time fee on funded loans from borrowers, and assessing an annual loan servicing fee to loan buyers. In case of a late loan, lenders can choose a collection agency, when the loan is at least one month late. If the collection agency can't collect payment from the borrower after four months of delinquency, the loan will be marked as "charge-off", and sold to a debt buyer. The borrower will not be able to borrow ever again from the platform, and since the company reports delinquencies to credit reporting agencies, this charge-off will adversely affect their credit report.

Though borrowers' credit grades, their debt to income ratios and other variables of their credit profiles are pulled from the credit rating agency Experian and displayed on their listings, transactions on the electronic marketplace still occur anonymously between fictious screen names. Internet transactions of this sort entail severe information asymmetries that cause problems of adverse selection and moral hazard. The description borrowers provide about themselves, their projects and even their employment status and income are mandatory information that is subject to moral hazard, because borrowers may be inclined to overemphasize their attributes in order to get their loan funded (at a better interest rate). The moral hazard problem is further exacerbated, since borrowers on the electronic marketplace have no collateral to loose. They therefore do not bear the full consequences of their actions and may act less carefully as they otherwise would. This may lead to adverse selection as described by Akerlof (1970) and can cause credit rationing in the sense of Stiglitz and Weiss (1981), negating the promising idea of the platform to make loans available for subprime risks.[1]

To mitigate information asymmetries, the platform introduced a group system, where the screening of potential borrowers and the monitoring of loan repayment can be delegated to designated group leaders. We find that these group leaders act as intermediaries between borrowers and lenders. This gives us a very rare opportunity to study financial transactions with and without the use of intermediaries and compare them directly with respect to their ability to mitigate informational asymmetries. Based on the pioneering work of Prescott (1997) and Diamond (1984), we hypothesise that these intermediaries contribute to reduce the prevalent credit risk in the online market. This hypothesis is put

[1]We find evidence for credit rationing in the market as only 40 percent of (even) the AA and A-graded loan listings get funded and the amount of small credit volumes exceeds larger loans by far. The median loan amount is $4,500 where the upper limit for a listing is $25,000.

to the test with probit models of the impact of group affiliation on borrower's repayment performance. We also investigate the potential bias induced by selection into the group contract and seek possible explanations for our estimates.

We find that, despite superior private information, these financial intermediaries perform worse than the average lender with respect to borrower selection. We attribute this to deliberately sending wrong signals. Bivariate probit estimates of the effect of group membership on loan default indicate positive self selection into grouploans. That is borrowers with worse observed and unobserved characteristics select into this contract form. We provide evidence that this is due to a missleading group reputation system that is driven by a short term incentive design, which was introduced by the platform to expand the market and has been discontinued in September 2007. We further find that after controlling for this group growth driven selection effect group affiliation per se significantly reduces the probability of loan default.

The structure of this paper is as follows. The next section provides an overview of the theoretical background of financial intermediation and sets out the hypotheses. The data and descriptive statistics are presented in the third section. In section four we present single-equation probit estimates of loan default models. In that section we also present a number of sensitivity tests for the single-equation model. Section five presents bivariate probit models that treat the decision to join a group as an endogenous variable. We discuss methodological shortcomings of our analysis in this section and present a brief summary and conclusions in the final section of the paper.

2 Theoretical Background

In this section we review the literature on group lending, financial intermediation and place group lending in the context of financial intermediation to derive our hypotheses.

2.1 Groups as Intermediaries

There is an emerging literature on group lending that examines the role of joint liable group members in overcoming asymmetries of information. In a widely cited article in the *World Bank Economic Review*, Stiglitz (1990) argues that a group lending contract, where borrowers from the same group are jointly responsible for each others' performance, can circumvent ex-ante moral hazard by inducing borrowers to monitor each others' choice of projects and to inflict penalties upon borrowers who have chosen excessively risky projects. Varian (1990) examines the important screening role groups may provide. That is, their use of prior knowledge about others to form groups, that can be harnessed to mitigate adverse selection. Besley and Coate (1995) examine the potential enforcement advantages groups may have. For example, social ostracism of defaulters is an option available to groups but not to outsiders. While groupmembers are *not* joint liable on the electronic marketplace, the group leader's financial rewards crucially depend on the repayment performance of his groupmembers. When studying two group lending programs in Eritrea, Hermes et al. (2005) find that peer monitoring by and social ties of the group leader may help to reduce moral hazard behaviour of group members, whereas they find no such link for other group members. Though their study is the first of this kind, it supports the assertion that some virtues of group lending are transferable to the electronic marketplace as well.

While we acknowledge that some of these features of group lending may play a role in the online marketplace's online group concept and control for them in our models, we abstract from them in the following discussion and follow the interpretation of groups as financial intermediaries (Prescott, 1997).

Groups on the electronic marketplace can be seen as intermediaries, because they act as delegated monitors. Diamond (1984) argues in a seminal paper that if monitoring is costly and lenders in a syndicate want to monitor a borrower, monitoring expenditures will either be inefficiently high, or lenders will have an incentive to free ride on the monitoring efforts of others and consequently no lender has an incentive to monitor. In this situation, an intermediary as a delegated monitor minimizes the costs of monitoring.

This argumentation is applicable to the online lending mechanism, because the capital of several lenders is syndicated into one loan and lenders face a large number of credit listings on the marketplace. Acquiring private information about credit listings, that allows lenders to better assess credit risk, requires time and is cost intensive. Group leaders can therefore realize significant economies of scale in producing information for the marketplace by acting as intermediaries and producing additional private information about credit listings within groups.

Bhattacharya and Chiesa (1995) show that intermediaries can solve another information problem prevalent on online marketplaces. When borrowers might be hesitant to disclose private information to a large number of lenders in a public financial market, an intermediary can act as facilitator of knowledge sharing whereby proprietary information is only disclosed to the intermediary. Groups therefore enable a better assessment of borrowers' credit quality by producing additional private information. We deduce:

Hypothesis 1: Group membership reduces default rates, because lenders are better able to discriminate risky from save types in the market for group loans than in the market for individual loans.

2.2 Financial Intermediation and Signaling

The reliability of information produced by an intermediary is a prevalent problem in the intermediation literature. Group leaders might recommend credit listings within their group without prior diligent screening. It may be difficult or impossible for potential lenders to distinguish good information from bad. This can lead to market failure in the platform, because entry is easy for groups offering poor information. With imperfect information on borrowers' credit quality, lenders can use publicly observable signals to assess credit risk as shown in the seminal works of Akerlof (1970), Spence (1973) and Rothschild and Stiglitz (1976).

On Proser Marketplace, group leaders can signal the credibility of their group's listings by placing a bid on it. Leland and Pyle (1977) show that the investment of the intermediary is an observable signal for information quality. However we know from auction theory that individual investment decisions on financial markets can be subject to herding behaviour. Individual decisions may not be based on adequate information but the behaviour of other market participants (Bikhchandani and Sharma, 2001). Anecdotal evidence from the platform shows, that group leaders made use of this effect to place a first bid with an exorbitant maximum rate to get the auction started, being aware of the fact that they will be bidded out of the auction as it proceeds. As we are only interested in the group leader's *investment*, as his fraction of the loan amount when the loan got funded, we derive the following hypothesis:

Hypothesis 2: A group leader's participating bid on a borrowers listing serves as a credible signal for information quality. The higher the fraction of the loan amount collaterized by the group leader, the less likely is a loan to default.

2.3 Financial Intermediation and Reputation

A second way for group leaders to credibly signal information quality is to build up a reputation for timely loan repayment. On October 18th, 2006, the electronic marketplace introduced a star rating (1 to 5 stars) as a formal reputation system to make groups' past conduct more transparent. The group rating is a measurement of a group's performance in paying back its loans in comparison to expected historical Experian default rates. So for a successful repayment of a high risk loan with credit grade HR, the group will build up more reputation than for the repayment of a prime risk, AA rated loan. The rating is calculated for groups that have at least 15 payments billed (had at least fifteen monthly loan repayments; be it by one borrower or more). The more billed payments are displayed with the star rating, the more stable a rating system should be.

The concept of reputation has brought forward a large body of literature. From a game theoretic perspective, a history of cooperation does not imply that there will be cooperation (or even greater cooperation) in the future (Sobel, 2002, p. 150). But Watson (1999) and Sobel (2006) build models of the formation of trust by allowing agents to build reputation through informative past transactions. The reputation built by shared information about past conduct is part of the information contained in a traditional credit rating. The role of information tacking systems like credit bureaus in following the behaviour of borrowers modelled by Klein (1992) is well acknowledged (MacLeod, 2007). Tirole (1996) also shows theoretically how a group's good reputation positively influences individual behaviour. This leads us to the next hypothesis:

Hypothesis 3: A borrower in an overperforming group is less likely to default on his loan. Further, a group rating that is more stable in the sense of a higher number of billed loans, reduces default risk.

2.4 The Potential of Sorting Behaviour

Given that lenders can discriminate between good and bad information with the help of the group reputation system, the same must hold for potential borrowers, because each group's star rating is publicly available. An overperforming group rating will now lead to a higher number of applicants to that group, seeking a group that promotes their listing with a high reputation.[2] The group leader can in turn be more selective in the application and pre-screening process and further improve the group's reputation by selecting better borrowers. This results in a virtuous circle that leads to assortative matching (Becker, 1973) between groups and applying borrowers.[3] This potential assortative matching leads to the following hypothesis:

[2]The pioneering study of Berger and Gleisner (2008) finds that an overperforming star rating significantly reduces borrowers' interest rates.

[3]Assortative matching is a concept used in group lending to overcome adverse selection through joint liable group members and local information (Ghatak, 1999).

Hypothesis 4: Borrowers with better observed and unobserved characteristics select into groups. There is negative selection into group contracts.

2.5 The Vitality of Incentives

By formulating these hypotheses, we must not forget that intermediation just shifts the cooperation problem between borrower and lender to a cooperation problem between intermediary and lender. Dependent on the incentive scheme, a group leader may still find it optimal to send misleading signals if their costs are below the possible short-term gain of cheating. During the period of our sample, the company had implemented a monetary incentive scheme for group leaders. The incentive scheme meets the two functions of a group leader.

First, group leaders are supposed to filter applying borrowers for credibility and are therefore rewarded a *payment reward* upon successful loan repayment. The payment reward is dependent on the borrower's credit grade. For AA to HR rated borrowers, 1 to 4 percent of the loan's monthly payment rate is awarded to the group leader upon borrower's timely repayment.[4] To ensure that the loan is not bad, the first three months' payment rewards are held back and paid to the group leader when the loan is paid in full. Should the loan default in the first three months, the accumulated repayment rewards of this loan are used to satisfy the creditors. We refer to the payment reward as the group leader's long term incentives to select credible borrowers based on local information and diligent screening.

Second, a *match reward* was introduced by the platform primarily to expand the market, using group leaders as marketeers. This reward might have set the right signals for group leaders to recruit new borrowers and help them get their listing funded, as can be seen in the historical growth of the number of group loans between February 2006 and September 2007 in Figure 1. But it created perverse incentives to get new borrowers funded without thoroughly screening them. Some groups had over 100 funded loans per month (see Figure 2 for the largest group). And this is without mentioning the unsuccessful listings and members joining these groups at this time.
Group leaders were then free to choose a fraction of the group leader reward they want to share with the borrower. This can be either 100 percent, i.e. the rewards are fully shared with the borrower or any fourth down to 0 percent, where the group leader receives the full rewards. The direction of action of this incentive scheme is not clear in advance,

[4]For extent and variation of the financial rewards please refer to Figure 3.

Figure 1: The Platform's Loan History

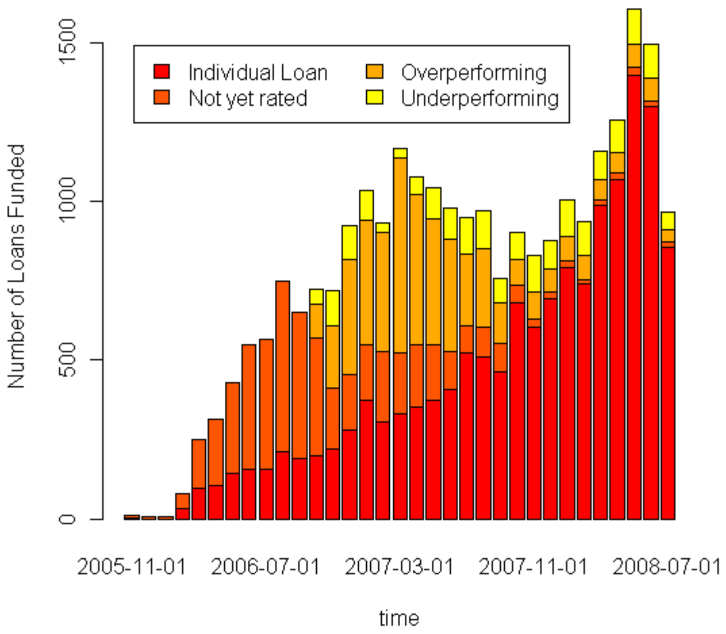


Figure 2: Largest Borrowers' Group Evolution

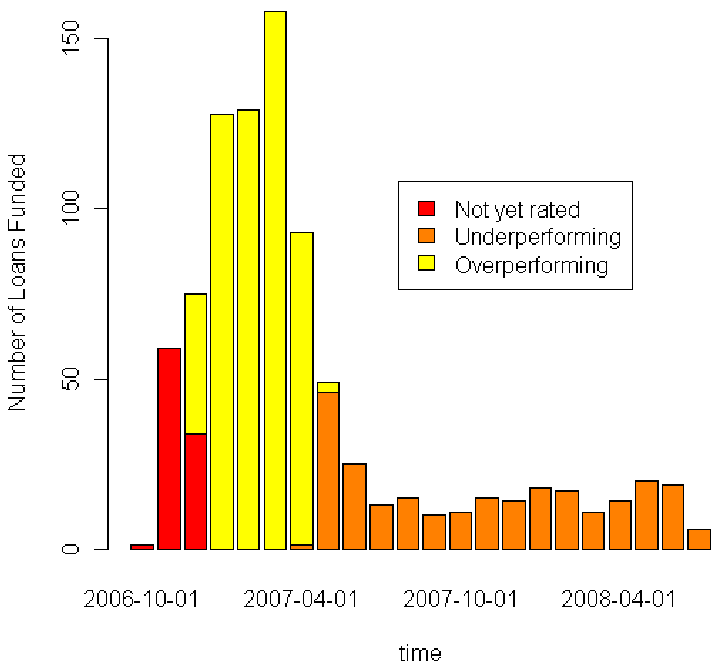
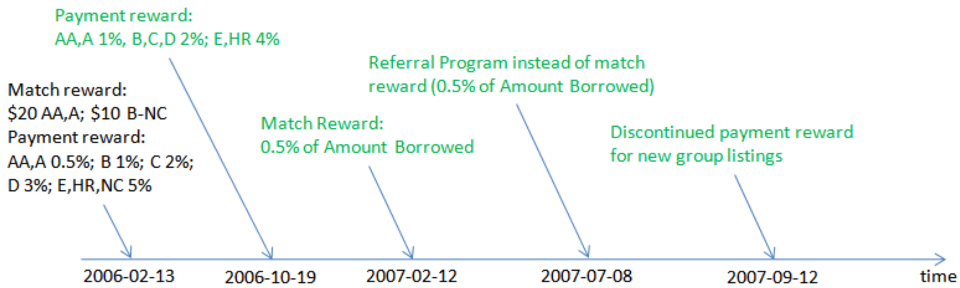


Figure 3: The Company's Reward Changes



but the design of these incentives seems to play a crucial role in determining the group leader's actions. We will get a clearer picture of the impact of the reward system in the empirics part in Section 5.

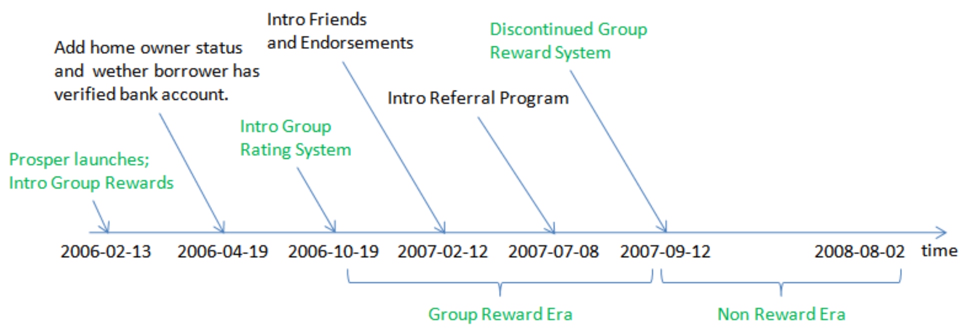
3 Data

The data used for this analysis comes from the platform's public and private data exports. As most of the variables in the snapshot of the platform are observed only at the observation date, and we are interested in the variables the day a loan got listed or funded, we used PERL based programs to pull historical variables from the site. We further replicated the group rating the day a listing is placed and the group leader reward rate of the group with the help of the formulas provided by the company on their homepage. The final sample consists of 10,217 loans, funded at the platform from the introduction of the group rating system on October 19th, 2006 until September 12th, 2007, when the group leader reward system was discontinued. We restrict the sample to this time horizon, because there were no notable policy changes on the platform that might bias our estimates (see Figure 4). We restrict the sample to those loans which have not been cancelled or repurchased by the company due to credit card or identity theft. We then consider only the loan performance in the 11th month loan cycle[5] and dichotomize the loan status into the categories "default" and "non default", where we consider a 4+ month late loan as "default" because we find that almost all of these loans defaulted in

[5]We do not use the loan performance at this point in time as given in the data export and control with the loans' age in months because it implies a paradox situation for defaulted loans. We want to estimate a model for loan default, when the loan got funded, so we can not feed our model with information that is available only thereafter. If a loan defaults in the 3rd loan cycle, we would set his loan age to 3 for all times. That is, we would use information about a loan's status to predict this status. We further do not use survival analysis, because the time to death (here: default) is restricted to the length of the loan term of 36 months in every case.

the past. Though this approach means ignoring valuable information, we find this is the best way to proceed. We check for robustness, using alternative measures of default in Section 5.5. Means and standard deviations of the independent variables are shown in Table 1, these variables can be categorized along the following four dimensions.

Figure 4: The Platform's Policy Regimes



3.1 Credit Profile

The most powerful variables to discriminate between defaulting and non defaulting borrowers are those from their individual credit profiles. The CreditGrade assigned to every borrower by the US based credit rating agency Experian ranges in 7 categories from AA to HR (high risk). The DebtToIncomeRatio is censored from above at 1000 percent which is only relevant for 225 loans and not displayed for 304 self-employed borrowers and 528 other loans. The variable IsBorrowerHomeowner is not available for 590 loans. The categorical variables EmploymentStatus and Income are self reported by the borrower at the time the listing is created. Further variables are the history of the borrower's delinquencies, inquiries and total credit lines and the length of his employment status.

- CreditGrade
- DebtToIncomeRatio
- IsBorrowerHomeowner
- EmploymentStatus
- Income
- DelinquenciesLast7Y
- InquiriesLast6Months
- TotalCreditLines
- LenghtStatusMonths

A broader Credit Profiles Object is available from the private data export but this information is only available for loans created from March 2007 on, which makes this data inadequate for our purposes.

3.2 Loanspecific Variables

Loanspecific variables that determine loan default are the AmountBorrowed and FundingOption. The latter is a binary variable that is 0 if the listing is open for the auction's full duration of 10 days and 1 if the listing closes as soon as it is funded 100 percent.

- AmountBorrowed
- FundingOption

3.3 Social Collateral and Self-Disclosure

The uniqueness of this dataset is that we have information about a number of social capital measures. One feature is the Endorsement function where every active member on the platform is allowed to write an Endorsement for a borrower's listing to make it more appealing to creditors. StateDiffGL is a binary that indicates if group leader and borrower live in the same state and puts the irrelevance of distance hypotheses of online markets to the test. BorrowerCity is an optional field on the borrower's listing that displays his city of residence as shown on his identity card. This variable allows us to control for the effect of self-disclosure on loan default.

The variables GLCol and GroupCol are the fractions of the AmountBorrowed that are financed, i.e. collaterized, by group leaders and group members respectively. These variables show if lending from groupmembers makes a difference with respect to repayment performance. PartAm/AmBorr gives us the ratio of a borrower's "deposits" and credits on the platform. Some groups have rigorous rules of conduct that oblige a borrower to become an active lender on the platform before applying for groupmembership or to reinvest a fraction of their LoanAmount. Evidence from credit cooperatives shows that borrower's deposits function as collateral and reduce default risk (Banerjee et al., 1994).

- Endorsement
- StateDiffGL
- BorrowerCity
- GLCol
- GroupCol
- PartAm/AmBorr

3.4 Group Characteristics

A group's capability to screen applying borrowers is essential for the model of financial intermediation to hold. A variable that allows insights into the quality of the screening process is GroupGrowth at the time the loan was funded, which is a measure of the number of loans that where funded in this group the month before the loan got funded.

The group rating is a 1 to 5 star based group rating, visible to every lender at the time the listing was created. GroupRatingBin is just a binary indicating if the group has over- or underperformed the benchmark given by the Experian historical default rate. The number of billed payments (NoBilled) indicates the stability of the group rating.

By building up reputation in the form of a high group rating, a group leader was able to make some money by charging fees, "group leader rewards", until the group reward system was discontinued on September 12th, 2007. The GLRewardPercentage is the portion of the borrower rate (sum of match and payment reward) that is paid to the group leader. Setting a higher GLRewardPercentage allows the group leader to capitalize on his efforts in building reputation, or leads group leaders to sell out their reputation.

Since the reputation system was discontinued in September 2007, which was effectively setting the GroupLeaderReward to zero, only 33 active groups have been founded – compared to 707 in the same time period before. Not surprisingly, the fraction of groups that no longer accepts new borrowers makes up 39 percent of the groups that ever had a loan.

- GroupGrowth
- GLRewardPercentage
- GroupRatingBin
- NoBilled

In the next section we will set up probit models of loan default, to test our hypothesis that group members have a better record of loan performance than individual borrowers.

Table 1: Means and Standard Deviations

	Sample		Group Loans		Individual Loans	
	mean	sd	mean	sd	mean	sd
GroupAffiliation	0.62	0.48	1.00	0.00	0.00	0.00
StatusBin	0.13	0.34	0.15	0.35	0.10	0.31
RateCap	0.24	0.09	0.23	0.09	0.24	0.09
FracGroupLoansInState	0.62	0.05	0.63	0.05	0.62	0.04
CreditGrade AA	0.10	0.31	0.09	0.26	0.15	0.36
CreditGrade A	0.10	0.30	0.08	0.27	0.13	0.33
CreditGrade B	0.13	0.33	0.11	0.31	0.15	0.36
CreditGrade C	0.18	0.38	0.17	0.38	0.18	0.39
CreditGrade D	0.19	0.39	0.19	0.39	0.18	0.38
CreditGrade E	0.14	0.34	0.15	0.36	0.12	0.32
CreditGrade HR	0.17	0.37	0.22	0.41	0.09	0.28
CreditGrade NC	0.00	0.06	0.00	0.07	0.00	0.05
DebtToIncomeRatio	0.44	1.37	0.50	1.50	0.35	1.11
DelinquenciesLast7Years	7.11	13.38	8.02	14.24	5.60	11.67
InquiriesLast6Months	3.49	4.53	3.77	4.84	3.03	3.93
TotalCreditLines	23.97	13.99	24.22	13.90	23.57	14.14
IsBorrowerHomeowner True	0.42	0.49	0.40	0.49	0.46	0.50
LengthStatusMonths	39.56	65.68	36.97	64.37	43.88	67.59
AmountBorrowed	6531.45	5849.49	6469.63	5730.36	6634.17	6041.58
EmploymentStatus Full-time	0.60	0.49	0.56	0.50	0.65	0.48
EmploymentStatus Not available	0.35	0.48	0.38	0.49	0.30	0.46
EmploymentStatus Not employed	0.01	0.08	0.01	0.08	0.01	0.08
EmploymentStatus Part-time	0.02	0.15	0.02	0.15	0.03	0.17
EmploymentStatus Retired	0.01	0.11	0.01	0.11	0.01	0.11
EmploymentStatus Self-employed	0.05	0.21	0.05	0.21	0.05	0.21
Income NotDisplayed	0.36	0.48	0.39	0.49	0.32	0.47
Income NotEmployed	0.00	0.07	0.01	0.08	0.00	0.06
Income $1-24k	0.10	0.28	0.09	0.28	0.09	0.28
Income $25-49k	0.25	0.43	0.25	0.43	0.25	0.43
Income $50-74k	0.16	0.37	0.15	0.36	0.18	0.38
Income $75-99k	0.07	0.26	0.06	0.24	0.08	0.28
Income $100k+	0.06	0.24	0.05	0.22	0.08	0.27
LenderRate	0.18	0.06	0.18	0.06	0.17	0.07
BorrowerRate	0.18	0.06	0.19	0.06	0.17	0.07
FundingOption Open For Duration	0.69	0.46	0.75	0.43	0.58	0.49
Endorsements	0.40	0.49	0.51	0.50	0.21	0.41
BorrowerCity	0.32	0.47	0.40	0.49	0.20	0.40
PartAm/AmBorr	0.02	0.73	0.00	0.05	0.04	1.19
GroupCol	–	–	0.01	0.05	–	–
GLCol	–	–	0.04	0.13	–	–
StateDiffGLSame	–	–	0.12	0.33	–	–
GLRewardPercentageOfBase	–	–	0.28	0.27	–	–
GroupGrowth	–	–	33.18	38.89	–	–
GroupRatingBin Underperforming	–	–	0.14	0.35	–	–
GroupRatingBin Overperforming	–	–	0.58	0.49	–	–
NoBilled	–	–	243.61	476.77	–	–
IsAcceptingNewMembersFalse	–	–	0.45	0.50	–	–
Observations	**10,217**		**6,378**		**3,839**	

Table 2: Correlation Matrix

	StatusBin	GroupAffiliation	RateCap	FracGroupLoansInState	CreditGradeAA	CreditGradeA	CreditGradeB	CreditGradeC	CreditGradeD	CreditGradeE	CreditGradeHR	CreditGradeNC	DebtToIncomeRatio	DelinquenciesLast7Years	InquiriesLast6Months	TotalCreditLines	IsBorrowerHomeowner	LengthStatusMonths	AmountBorrowed	FundingOption	BorrowerCity	Endorsements
GroupAffiliation	0.06																					
RateCap	0	-0.02																				
FracGroupLoansInState	0.01	0.09	0.13																			
CreditGradeAA	-0.11	-0.12	-0.02	-0.03																		
CreditGradeA	-0.09	-0.08	0	-0.02	-0.11																	
CreditGradeB	-0.07	-0.07	0.01	-0.02	-0.13	-0.12																
CreditGradeC	-0.04	-0.02	0	-0.03	-0.16	-0.15	-0.18															
CreditGradeD	-0.02	0.02	0.02	0	-0.16	-0.16	-0.18	-0.22														
CreditGradeE	0.06	0.05	-0.01	0.02	-0.14	-0.13	-0.15	-0.19	-0.19													
CreditGradeHR	0.22	0.17	-0.01	0.06	-0.15	-0.15	-0.17	-0.21	-0.22	-0.18												
CreditGradeNC	0.05	0.02	-0.01	0.01	-0.02	-0.02	-0.02	-0.03	-0.03	-0.02	-0.03											
DebtToIncomeRatio	0.02	0.05	-0.01	0.01	-0.01	0.02	0.02	0.01	0.03	-0.02	-0.04	-0.01										
DelinquenciesLast7Years	0.09	0.09	0.01	0.03	-0.16	-0.13	-0.11	-0.04	0.03	0.18	0.18	-0.03	-0.06									
InquiriesLast6Months	0.17	0.08	0	0.01	-0.13	-0.1	-0.04	-0.01	0.01	0.09	0.14	-0.01	0.02	0.07								
TotalCreditLines	-0.01	0.02	0.02	0.02	0.05	0	0.04	0.04	0.01	0.07	-0.16	-0.09	0.01	0.19	0.17							
IsBorrowerHomeowner	-0.05	-0.06	0.03	0	0.23	0.09	0.1	0.09	-0.1	-0.12	-0.2	-0.05	0.03	-0.07	0.07	0.35						
LengthStatusMonths	-0.05	-0.05	0.03	-0.04	0.05	0.02	0.05	0.06	0.01	-0.06	-0.12	-0.04	0	0.01	-0.01	0.18	0.18					
AmountBorrowed	-0.02	-0.01	0.05	-0.03	0.13	0.18	0.18	0.1	-0.04	-0.17	-0.3	-0.04	0.07	-0.17	0.03	0.14	0.25	0.1				
FundingOption	-0.12	0.18	-0.01	0	0.13	0.08	0.06	0.01	-0.04	-0.09	-0.11	-0.03	-0.02	-0.08	-0.08	-0.02	0.04	0.01	0.07			
BorrowerCity	0.01	0.21	-0.02	0.06	-0.03	-0.03	-0.04	-0.03	-0.02	0.03	0.1	0.01	0	0.02	0.04	-0.03	-0.07	-0.11	-0.05	0.04		
Endorsements	-0.02	0.29	0.02	0.01	-0.05	-0.01	-0.02	0	0.04	0	0.02	-0.02	0.05	0	0.02	0.01	-0.02	0.09	0.06	0.17	0.05	
PartAm	-0.01	-0.02	-0.02	-0.03	0.05	0	0	-0.01	-0.01	-0.01	-0.01	0	0	-0.01	-0.01	0	0.01	-0.01	-0.02	-0.01	0.01	0.01

4 Probit Models of Loan Performance

4.1 Single-Equation Probit Models

We set up the following model to estimate the probability of a given loan to default. Let the indicator variable $Y_i = 1$ if borrower i defaulted on his loan, and let $Y_i = 0$ otherwise. The model is described by the latent variable model

$$Y_i^* \quad = \quad X_i\beta + G_i\delta + u_i, \tag{1}$$

where Y_i^* is a latent variable that indicates a score value of loan default, X_i is a vector of individual characteristics, G_i is the group affiliation dummy, and u_i is a normally distributed random error with zero mean and unit variance. Borrowers only default on their loan, if their score of loan default exceeds a threshold c,

$$\begin{cases} Y_i = 1 & \text{if } Y_i^* > c \\ Y_i = 0 & \text{if } Y_i^* \leq c \end{cases}$$

and thus the probability that a loan defaults is

$$P(Y_i = 1) \quad = \quad P(X_i\beta + G_i\delta + u_i > c) = \Phi(X_i\beta + G_i\delta),$$

where Φ is the evaluation of the standard normal cumulative distribution function.

For the first single equation probit model, we consider all variables from the borrower's credit profile, but leave out those variables that are subject to the borrowers' contract choice – except the binary of interest: GroupAffilition. That is, we omit all group characteristics, because they may be endogenous, since they are subject to the borrower's choice. The probit estimates in Table 3 show that, after controlling for other variables in the credit profile, GroupAffilition has no significant impact on the loan status.

The other results in Table 3 are consistent with the literature in this field (Avery et al., 1996). One exception is the binary IsBorrowerHomeowner, that we would have expected to have a negative impact on loan default. One reasonable explanation for our estimate are the antecedents of the subprime mortgage crisis which became apparent throughout the period of our sample in 2007. Homeowners who were not able to serve their bank loans may have chosen the electronic marketplace to reschedule their debts. Thus the credit quality of homeowners might have been considerably worse than that of other borrowers on the online market.

Table 3: Probit of Loan Default

Single Equation Probit

	Probit		Probit (robust)	
	Estimate	Std. Error	Estimate	Std. Error
(Intercept)	-2.5530	(0.1300)***	-2.1420	(0.1423)***
GroupAffiliation	-0.0442	(0.0370)	0.0716	(0.0414).
CreditGrade A	0.3293	(0.1257)**	0.2298	(0.1345).
CreditGrade B	0.5924	(0.1147)***	0.4537	(0.1233)***
CreditGrade C	0.9297	(0.1092)***	0.7448	(0.1184)***
CreditGrade D	1.0770	(0.1108)***	0.8837	(0.1204)***
CreditGrade E	1.4090	(0.1146)***	1.1990	(0.1248)***
CreditGrade HR	1.8130	(0.1151)***	1.5910	(0.1258)***
CreditGrade NC	2.2060	(0.2364)***	1.9050	(0.2426)***
DebtToIncomeRatio	0.0218	(0.0127).	0.0238	(0.0130).
DelinquenciesLast7Years	0.0028	(0.0012)*	0.0021	(0.0012).
InquiriesLast6Months	0.0296	(0.0035)***	0.0295	(0.0035)***
TotalCreditLines	-0.0005	(0.0014)	-0.0010	(0.0014)
IsBorrowerHomeowner True	0.0716	(0.0401).	0.0833	(0.0408)*
LengthStatusMonths	-0.0005	(0.0003)	-0.0007	(0.0003)*
AmountBorrowed	0.0000	(0.0000)***	0.0000	(0.0000)***
Income NotDisplayed	-0.1599	(0.1815)	-0.1968	(0.1864)
Income NotEmployed	-0.0065	(0.4803)	0.0702	(0.4858)
Income $25-49k	-0.0304	(0.0732)	-0.0178	(0.0739)
Income $50-74k	-0.1222	(0.0814)	-0.0949	(0.0824)
Income $75-99k	-0.2110	(0.1009)*	-0.1707	(0.1028).
Income $100k+	-0.0742	(0.1041)	-0.0369	(0.1069)
EmploymentStatus Not available	0.1028	(0.1770)	0.0923	(0.1825)
EmploymentStatus Not employed	0.2516	(0.4248)	0.1194	(0.4298)
EmploymentStatus Part-time	-0.0900	(0.1297)	-0.1151	(0.1315)
EmploymentStatus Retired	-0.0303	(0.1739)	-0.0178	(0.1763)
EmploymentStatus Self-employed	0.2373	(0.0812)**	0.2333	(0.0828)**
FundingOption OpenForDuration			-0.2099	(0.0375)***
Endorsements			-0.1244	(0.0394)**
BorrowerCity			-0.0691	(0.0380).
PartAm/AmBorr			-0.8875	(0.0857)***
Observations	10,217		10,217	
AIC	7,028		6,820	

Notes: Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

4.2 Potential Omitted Variable Bias

In this section we test for robustness of the results. Our primary concern here is that we may have omitted important (measurable) characteristics of the borrower that are correlated with the group dummy and that, as a consequence, we have understated the benefits of group affiliation. The data export provides us with some more variables that we were hesitant to include in the model, not because they are subject to the borrower's decision to join a group or to list individual, but because they are conditional on this decision.

A group leader's primary job is to help the borrower to get his listing funded. The borrower's choice of the FundingOption, his choice to disclose his city of residence (BorrowerCity) and the endorsements on his listing are determined after his decision to list with a group and may therefore be influenced by the group leader. When introducing these variables into our model, the estimate for the GroupAffiliation dummy becomes positive (see Table 3). The significance of this change in sign is not surprising, given that all three variables are positively correlated with the group dummy and have a negative impact on loan default. Choosing to leave the listing open for the full duration of the auction signals a borrower's interest in a lower interest rate (Klemperer, 2004) and therefore in repaying the loan. Sharing his city of residence works as self-disclosure and therefore reduces uncertainty in the electronic marketplace (Tidwell and Walther, 2002). Group leaders, who have a better grasp of the market than rookie borrowers seem to advise their members to keep their hands off the quick funding option and display as many details as possible to get their loans funded (see Table 1). Further, either group leaders or group members seem to endorse borrowers in their own group, because group loans exhibit twice the number of endorsements that individual loans do.

4.3 Group Selectivity or Self-Selection?

We now turn our attention to the concern that we have omitted important unobservable characteristics of the borrower that are correlated with the group dummy. On the electronic marketplace, a borrower first has to apply for group membership and to be accepted by the group leader to start his listing with a certain group. Group leaders are therefore free to select their members with respect to credibility, amongst others. Thus, part of the GroupAffiliation effect could be due to the way group leaders choose their members. As we do not observe the selection process but only the result, we can expect our estimates to be biased because of unobserved omitted variables that drive the selection into groups if they also impact loan default (i.e. if group leaders are successfully selecting their members with respect to credibility as derived in *Hypothesis 4*).

To see the argument from the opposite angle, consider a start-up that seeks access to finance on the online lending market, for reasons addressed in the Introduction of this paper. One considerable problem of this entrepreneur is that he did not yet have the opportunity to build up reputation in the form of an excellent credit rating. Breuer (1995) claims that for young firms, reputation building often does not pay because of their low probability of continuation. He suggests that start-ups are therefore more likely to make use of the services of an intermediary to avoid immanent incentive problems. The same reasoning may hold for private borrowers who – just as the entrepreneur – have an irregular income or a missing credit history. They will be more likely to self-select into groups. However they are only group loans in our sample if the groupleader accepted them.

From these two examples it is obvious that the selection process is not an unilateral, but instead a bilateral matching process that takes place in a sequential way. Membership in a particular group always requires the borrower's application as well as the group leader's acceptance. We will abstract from this complexity for the rest of this discussion and interpret the selection process very cautiously, though we acknowledge that there would be more appropriate methods to handle the properties of our data.[6]

Following this perception, a probit model is a very simplified selection equation. For the moment we even go one step below. We run a simple OLS to estimate the probability of selecting into a group. We need this model to test GroupAffiliation for endogeneity using a test proposed by Rivers and Vuong (1988). This test may save us the tricky interpretation of the selection effects if it does not allow us to reject the null that GroupAffiliation is exogenous.

The logic of this test is very much like a standard Hausman test for endogeneity but with a structural equation that is a probit instead of an OLS. The idea is to compare the standard probit with a two-stage instrumental variable (IV) probit. If G_i is uncorrelated with u_i, the probit and the IV probit should differ only by sampling error. The model

[6] Sørensen (2007) proposes a model based on the two stage Heckman selection model, where the selection equation controls for sorting and is based on a two-sided matching model known as the college admissions model (see Gale and Shapley, 1962). Besides the computational complexity of this model, that necessitates considerable compromises in model specification, the problem of a dichotomous dependent variable in the structural equation has, to the best of our knowledge, not yet been addressed.

we set up is:

$$
\begin{aligned}
G_i &= X_i\gamma + IV_i\eta + v_i & (2)\\
P(Y_i = 1) &= P(X_i\beta + G_i\delta + v_i\alpha + u_i > c), & (3)
\end{aligned}
$$

where Equation (2) is an OLS with instrumental variables (IV) and the structural model in Equation (3) is our well known probit model of loan default with the residuals of the selection equation v_i as an extra regressor. The t-test of α is then a valid test for exogeneity of G_i (Wooldridge, 2002, p. 474).[7]

Instruments

To run the IV probit, we need at least one IV that must be correlated with G_i but must not be correlated with Y_i. Two possible candidates are:

- RateCap
- FracGroupLoansInState.

RateCap contains the maximum interest rate that can be charged for private loans in the borrower's state (state interest rate cap). This limit is defined in the state level usury law, but companies like the electronic marketplace have their own state specific rules. There has been one major change in the interest rate limits, when the platform went from interest rates to annual percentage rate (APR) caps in May 2007.[8] We replicated all the historical RateCap changes on the platform for the full time period of the sample.

The variation of RateCaps, following a strict schedule across states, time and loan categories that we can control for, makes RateCaps a perfect instrument for the selection process into group or individual loans. The rationale behind it is that borrowers living in a state with a low rate cap should have a higher propensity to join a group, because groupmembership significantly reduces interest rates *ceteris paribus* as shown in studies by Freedman and Jin (2008) and Berger and Gleisner (2008). Imagine a high risk borrower from Texas, where the interest rate cap is 10 percent for private loans and 18 percent for business loans. To get his loan funded, he has to convince potential lenders that he is worth a lower risk premium. One way to do this is to capitalize on a group's

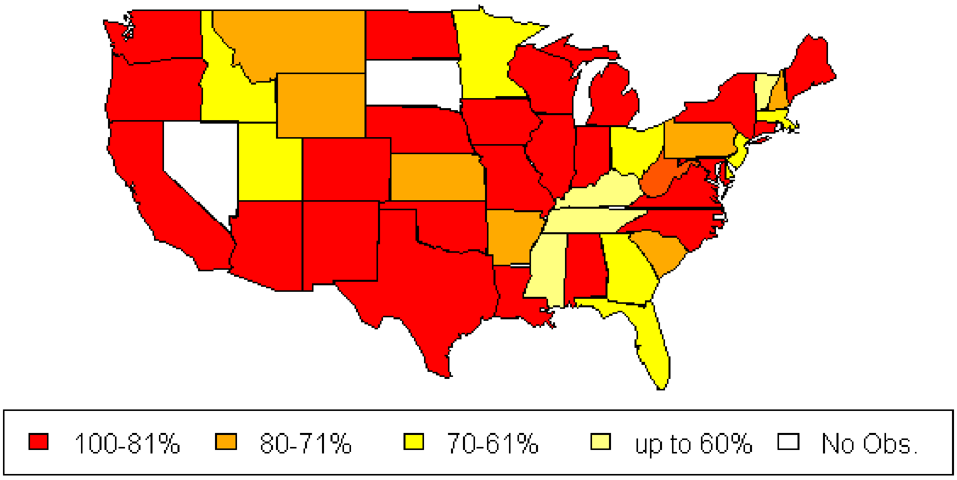
[7]Though Rivers and Vuong (1988) proposed this procedure to test for endogeneity in a probit model with possibly endogenous *continuous* explanatory variables, this test can also be applied to binary variables because under the null hypothesis that G_i is exogenous, the distribution of the first stage equation plays no role (Wooldridge, 2002, p. 474).

[8]By affiliating with Web Bank on April 15th, 2008, borrowers nationwide (except in Texas and South Dakota) can offer a maximum interest rate of 36 percent which lenders can then bid down.

reputation. The group system therefore is a way to overcome credit rationing induced by low RateCaps.

While the selection process significantly depends on the RateCap faced by the borrower, the loan performance is independent of this covariate after controlling for loanspecific variables and the borrower's credit profile. The same holds for the fraction of grouploans in the borrower's state (FracGroupLoansInState). This covariate controls for other statespecific characteristics (see Figure 5 for the dispersion of this measure across the fifty US states). While RateCap also captures time effects of the decision to join a group, FracGroupLoansInState solely captures geographical and state specific aspects.

Figure 5: Fraction of Group Loans Across US States



Running the IV probit with these two instruments yields a slightly significant t-value (1.75) for α.[9] Though the exact value of the t-statistic is not meaningful if G_i and u_i are correlated, because apart from the null, normality of v_i is crucial, it gives reasoning to track the endogeneity problem with more appropriate methods in the next section.

5 Bivariate Probit Models

5.1 Why not a Matching Method?

The best evidence for loan performance of individual loans versus group loans would come from well-designed, deliberate experiments in which loan contracts are varied but everything else is kept the same. This can be achieved in a lab setting (see Abbink et al.,

[9]We will address the validity of our instruments in the next section.

2006) but is very difficult to conduct in the field. Karlan (2007) makes use of a quasi-random group formation process by the microfinance institute FINCA in Peru, where applicants sign up in a list and every 30 names the list is closed and a group is formed.

Gomez and Santor (2003) control for borrowers' self selection into group loans with the help of matching methods when estimating the treatment effect of group affiliation in Calmeadow's microfinance program in Canada. Instead of matching pairs of borrowers along conditional variables, they are matched along a propensity score – the probability that the borrower selected into the treatment (see Rosenbaum and Rubin, 1983). The limitation of utilizing the propensity score as a measure of comparability is determined by the availability of sufficient conditioning variables. 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 (Smith and Todd, 2001). This method is hence not applicable in our case for two main reasons. First, although our data set has rich information about social capital measures and group characteristics, we do not observe any demographic variables of our borrowers, except the information contained in Experian's credit profile. This will lead to a poor measurement of the decision to participate in the program, 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. Second, we do not use matching methods because of their limitation on observable characteristics. If we want to test the model of intermediation, we must, by definition, expect group leaders to screen and select their group members based on local information which is not observed on the platform. If selection was solely dependent on observables, the role of financial intermediaries screening borrowers ex ante would be invalid.

5.2 The Bivariate Probit with Sample Selection

Resorting to the literature on treatment effects when the outcome of interest is binary, we make use of a recursive bivariate probit model. Using this method allows us to control for ex ante screening and selection into the group (*Hypothesis 4*) and to separate the single effect of being in a group on loan performance (*Hypothesis 1*).[10]

The bivariate probit with endogenous dummy model belongs to the general class of simultaneous equation models with both continuous and discrete endogenous variables

[10] The interpretation is the same as with a Heckman two-stage correction, but using the latter method may produce inconsistent estimates because our structural equation is not linear (Wooldridge, 2002, p. 478).

introduced by Heckman (1978). The recursive structure builds on a first reduced form equation for the potentially endogenous dummy GroupAffiliation (G_i) and a second structural form equation determining loan default:

$$G_i^* = Z_i\gamma + v_i \tag{4}$$

$$Y_i^* = X_i\beta + G_i\delta + u_i, \tag{5}$$

where G_i^* and Y_i^* are latents, G_i and Y_i are dycotomous variables observed and G_i is following the rule

$$\begin{cases} G_i = 1 & \text{if } G_i^* > 0 \\ G_i = 0 & \text{if } G_i^* \leq 0, \end{cases}$$

that is a borrower selects into a group if his expected net benefit of joining a group is positive. The error terms are assumed to be independently and identical distributed as bivariate normal:

$$\begin{pmatrix} u_i \\ v_i \end{pmatrix} \sim i.i.d.N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix}\right).$$

A widespread opinion in the literature is that the parameters of the structural equation are not identified unless Z_i includes at least one variable not contained in X_i (as in linear simultaneous equations for fully observed endogenous variables). This assertion stated by Maddala (1983) has been contested by Wilde (2000), who shows that exlusion restrictions are not needed provided there is one varying exogenous regressor in each equation. Therefore Z_i and X_i are not necessarily distinct design matrices. The parameter vector $(\beta,\ \gamma,\ \rho)$ can be estimated by maximum likelihood. The sample likelihood function, that has to be maximized resorting to numerical methods is given by

$$ln\ L(\beta, \gamma, \rho) = \sum_{i=1}^{n} d_{11} lnP_i^{11} + d_{10} lnP_i^{10} + d_{01} lnP_i^{01} + d_{00} lnP_i^{00},$$

where

$$d_{11} = G_i Y_i; d_{10} = G_i(1 - Y_i); d_{01} = (1 - G_i)Y_i; d_{00} = (1 - G_i)(1 - Y_i)$$

and

$$\begin{aligned}
P_i^{11} &= P(G_i = 1, Y_i = 1 | Z_i, X_i) = \Phi_2(Z_i\gamma, X_i\beta + \delta_i, \rho) \\
P_i^{10} &= \Phi_2(Z_i\gamma, -X_i\beta - \delta_i, -\rho) \\
P_i^{01} &= \Phi_2(-Z_i\gamma, X_i\beta, -\rho) \\
P_i^{00} &= \Phi_2(-Z_i\gamma, -X_i\beta, \rho)
\end{aligned}$$

and $\Phi_2(\cdot, \cdot, \rho)$ is the bivariate normal distribution function of the model error terms. To make this notation clearer, let us consider the first of four possible states of the world $G_i = 0$ or 1, and $Y_i = 0$ or 1, as notated above.

The likelihood to observe a borrower i who is group member ($G_i = 1$) and defaults on his loan ($Y_i = 1$) is given by P_i^{11}. The dummy d_{11} takes the value 1 only if $G_i = 1$ and $Y_i = 1$, because for this borrower we only observe this one and only state of the world. Consequently, the three other dummies are 0. P_i^{11} is just the chance that our borrower selects into a group ($v_i > -Z_i\gamma$) and defaults on his loan ($u_i > -X_i\beta - \delta$) as modelled in Equations (4) and (5) respectively.

Let us have a look at the correlation parameter ρ between the error terms of Equations (4) and (5). If we find that $\rho = 0$, then G_i is independent of u_i and the single-equation probit model we estimated in Section 4 is an appropriate approach to model our observations. If $\rho \neq 0$, then G_i is dependent on u_i, because u_i is correlated with v_i, and v_i comes into Equation (4) that determines G_i. In the following discussion, we interpret a positive correlation of the error terms as a positive self-selection of borrowers into groups. That is, borrowers with *worse* unobservable characteristics select into this contract form. The reasoning behind this interpretation is that unobservable characteristics of the borrower that make him select into a group, are captured by the error term v_i and positively correlated with the error term u_i. That is, if we omit these variables that have a positive effect on loan default (make a borrower more likely to default) in the structural equation, our estimates would be biased upwards. Correcting for this bias with an simultaneous estimation of the two equations therefore generates consistent estimates.

5.3 Results

We first estimate the bivariate probit without instruments, making use of the Wilde (2000) findings and then evaluate the same model using RateCap and FracGroupLoansInState as instrumental variables.

The bivariate probit without instruments in Table 6 shows a highly significant negative effect of GroupAffiliation on loan default and when evaluating the correlation of the error terms we find that ρ is considerably larger than null (0.29). The ρ estimate signifies a selection of borrowers with worse characteristics into group contracts. This finding, which is consistent with the positive coefficient of v_i in the Rivers and Vuong (1988) test, would mean that we have to reject our *Hypothesis 4*.

Running the same bivariate probit with instruments does not have much impact on our results. As expected, the two instruments do an excelent job in explaining the selection process (see Table 5), but the coefficient of GroupAffiliation is still highly significant and a ρ of 0.18 is still distinct different from null. Even the robustness check with the three possibly endogenous variables FundingOption, BorrowerCity and Endorsements that lead to an upwards shift in the coefficient of GroupAffiliation in the single-equation probit does not change the results in this case (see Table 4).

Table 4: Bivariate Probit of Loan Default – Robustness Check

Selection Equation

	without Instruments		with Instruments	
	Estimate	Std. Error	Estimate	Std. Error
RateCap			-0.4520	(0.1476)**
FracGroupLoansInState			2.3653	(0.2942)***
Controls	YES		YES	

Outcome Equation

	without Instruments		with Instruments	
	Estimate	Std. Error	Estimate	Std. Error
GroupAffiliation	-0.5754	(0.0390)***	-0.1617	(0.0407)***
Controls	YES		YES	
FundingOptionOpen For Duration	-0.2051	(0.0357)***	-0.2106	(0.0371)***
BorrowerCity	-0.0666	(0.0375)*	-0.0683	(0.0381)*
Endorsements	-0.1183	(0.0386)**	-0.1234	(0.0394)***
PartAm/AmBorr	-0.8549	(0.0767)***	-0.8854	(0.0844)***
Observations	10,217		10,217	
ATE GroupAffiliation	-0.0789	(0.0815)	-0.0203	(0.0216)
ρ	0.3743		0.1092	

Notes: Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Table 5: Bivariate Probit of Loan Default – Selection Equation

Selection Equation

	without Instruments		with Instruments	
	Estimate	Std. Error	Estimate	Std. Error
(Intercept):1	-0.4065	(0.0698)***	-1.7732	(0.1932)***
RateCap			-0.4491	(-0.1473)**
FracGroupLoansInState			2.3762	(0.2938)***
CreditGrade A	0.0765	(0.0565).	0.0729	(0.0567).
CreditGrade B	0.1650	(0.0534)**	0.1645	(0.0536)**
CreditGrade C	0.3569	(0.0507)***	0.3576	(0.0509)***
CreditGrade D	0.4655	(0.0522)***	0.4634	(0.0524)***
CreditGrade E	0.5756	(0.0581)***	0.5725	(0.0583)***
CreditGrade HR	1.0204	(0.0595)***	1.0085	(0.0597)***
CreditGrade NC	1.0260	(0.2352)***	0.9948	(0.2351)***
DebtToIncomeRatio	0.0503	(0.0113)***	0.0496	(0.0113)***
DelinquenciesLast7Years	0.0022	(0.0011)*	0.0022	(0.0011)*
InquiriesLast6Months	0.0047	(0.0032).	0.0053	(0.0032).
TotalCreditLines	0.0053	(0.0011)***	0.0051	(0.0011)***
IsBorrowerHomeowner True	-0.0409	(0.0304).	-0.0401	(0.0305).
LengthStatusMonths	-0.0002	(0.0002)	-0.0002	(0.0002)
AmountBorrowed	0.0000	(0.0000)***	0.0000	(0.0000)***
Income NotDisplayed	-0.2234	(0.1185)*	-0.2160	(0.1189)*
Income NotEmployed	0.5895	(0.3676).	0.5441	(0.3704).
Income $25-49k	0.0315	(0.0563)	0.0410	(0.0564)
Income $50-74k	-0.0492	(0.0616)	-0.0479	(0.0617)
Income $75-99k	-0.1079	(0.0722).	-0.0962	(0.0724).
Income $100k+	-0.2596	(0.0763)***	-0.2573	(0.0765)***
EmploymentStatus Not available	0.3209	(0.1138)**	0.2889	(0.1143)**
EmploymentStatus Not employed	-0.2534	(0.3068)	-0.2310	(0.3097)
EmploymentStatus Part-time	-0.0527	(0.0883)	-0.0493	(0.0885)
EmploymentStatus Retired	0.1057	(0.1187)	0.1160	(0.1191)
EmploymentStatus Self-employed	0.1358	(0.0642)*	0.1304	(0.0644)*

Notes: Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Table 6: Bivariate Probit of Loan Default – Outcome Equation

Outcome Equation

	without Instruments		with Instruments	
	Estimate	Std. Error	Estimate	Std. Error
(Intercept):2	-2.3010	(0.1212)***	-2.4099	(0.1260)***
(Intercept):3	0.6130	(0.0473)***	0.3715	(0.0462)***
GroupAffiliation	-0.5519	(0.0354)***	-0.3769	(0.0359)***
CreditGrade A	0.3351	(0.1161)**	0.3360	(0.1214)**
CreditGrade B	0.6083	(0.1062)***	0.6083	(0.1109)***
CreditGrade C	0.9739	(0.1011)***	0.9673	(0.1057)***
CreditGrade D	1.1377	(0.1027)***	1.1267	(0.1073)***
CreditGrade E	1.4815	(0.1069)***	1.4690	(0.1113)***
CreditGrade HR	1.9451	(0.1078)***	1.9157	(0.1120)***
CreditGrade NC	2.3334	(0.2338)***	2.3074	(0.2352)***
DebtToIncomeRatio	0.0289	(0.0126)*	0.0266	(0.0126)*
DelinquenciesLast7Years	0.0031	(0.0012)**	0.0030	(0.0012)**
InquiriesLast6Months	0.0297	(0.0035)***	0.0299	(0.0035)***
TotalCreditLines	0.0004	(0.0014)	0.0001	(0.0014)
IsBorrowerHomeowner True	0.0641	(0.0394).	0.0674	(0.0398)*
LengthStatusMonths	-0.0005	(0.0003)*	-0.0005	(0.0003).
AmountBorrowed	0.0000	(0.0000)***	0.0000	(0.0000)***
Income NotDisplayed	-0.1943	(0.1760)	-0.1839	(0.1791)
Income NotEmployed	0.0879	(0.4743)	0.0542	(0.4781)
Income $25-49k	-0.0248	(0.0719)	-0.0270	(0.0726)
Income $50-74k	-0.1291	(0.0799).	-0.1277	(0.0807).
Income $75-99k	-0.2264	(0.0986)*	-0.2239	(0.0999)*
Income $100k+	-0.1218	(0.1022)	-0.1066	(0.1033)
EmploymentStatus Not available	0.1537	(0.1714)	0.1375	(0.1745)
EmploymentStatus Not employed	0.1973	(0.4187)	0.2207	(0.4226)
EmploymentStatus Part-time	-0.0964	(0.1260)	-0.0950	(0.1280)
EmploymentStatus Retired	-0.0108	(0.1690)	-0.0178	(0.1718)
EmploymentStatus Self-employed	0.2558	(0.0803)***	0.2518	(0.0808)***
Observations	10,217		10,217	
ATE GroupAffiliation	-0.0787	(0.0774)	-0.0519	(0.0517)
ρ	0.2973		0.1836	

Notes: Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

These are striking results that challenge the theory derived in the second section and possibly question the validity of the reputation system that was supposed to create that virtuous circle of group selectivity and loan performance. Though we are impatient to disclose the secret by analyzing the heterogeneity in the treatment effect of GroupAffiliation, we first turn to some robustness and validity checks of our model. We first test for the validity of our instruments, then check the definition of our dependent variable for robustness and finally propose an explanation for the counterintuitive rejection of *Hypothesis 4*.

5.4 Validity of the Instruments

Angrist (1991) showed in a Monte Carlo study that if we ignore the fact that the dependent variable is dichotomous and estimate

$$Y_i = X_i\beta + G_i\delta + u_i$$

with instrumental variables (IV), the IV estimate of δ is very close to the estimated average treatment effects (ATE) calculated in a bivariate probit model. We make use of these results, as the ATE of GroupAffiliation in Table 6, derived as $1/n \sum_i [\Phi(X_i\beta + \delta) - \Phi(X_i\beta)]$, is very close to the coefficient of GroupAffiliation in the heteroscedasticity corrected 2SLS in Table 7.

With more instruments than we need to identify the 2SLS system, we can test wether our instruments are valid in the sense that they are uncorrelated with the error term in the structural equation. We conduct a Sargan test of overidentifying restrictions as described in Wooldridge (2002, p. 122) to test the joint null hypothesis that our model is correctly specified and that the (two) instruments used are valid. In a 2SLS model, the test statistic is constructed by regressing the residuals of the structural model on all the exogenous variables in the system. The test statistic nR^2 is then $\chi^2(q)$ distributed where n is the number of observations and q the number of extra instruments. With a p-value of 0.18 in the last row of Table 7, we fail to reject the joint null of correct model specification and validity of our instruments, and we can thus have some confidence in the overall set of instruments used.

Table 7: 2 Stage Least Squares

1st Stage Equation

	Estimate	Std. Error
RateCap	-0.1664	(0.0524)**
FracGroupLoansInState	0.8224	(0.1025)***
Controls	YES	
R^2	0.0748	
$F_{27,10189}$	30.52	

2nd Stage Equation

	Estimate	Std. Error
1st step fitted.values	-0.1292	(0.0834)
Controls	YES	
R^2	0.0927	
$F_{27,10189}$	40.05	
$\chi^2_{10217,1}$	0.0520	

Although the Angrist (1991) results allow us to accurately estimate the ATE of the bivariate probit with 2SLS, we admit that it is not clear if the assumptions necessary to perform the Sargan test of overidentifying restrictions are met when both G_i and Y_i are binary. We follow Evans and Schwab (1995) here in that this class of tests is the best available diagnostic.

5.5 Robustness Check with Alternative Meassures of the Dependent Variable

As a final sensitivity test, we ask wether our results are robust to alternative definitions of the dependent variable. We have reestimated our models allowing for more or less restrictive thresholds for the latent variable to indicate loan default. We shift from originally 4+ months late down to three and two months late and also considered only delinquency as indicator of loan default. The results are shown in Table 8. While the bivariate probit without instruments confirms the robustness of our estimates, we realize some problems with the IV model. These difficulties can be addressed to computational problems of R's binom2.rho algorithm to converge. The last model in Table 8 did not converge, while the estimation of the other three models in the lower part of Table 8 converged in up to 10 iterations and give us confidence in the robustness of the IV bivariate probit estimates.

Table 8: Definition of the Dependent Variable

Bivariate Probit without instruments

Definition	Estimate	Std. Error	ρ	ATE (Std. Error)	Avg. Default
2 months late	-0.2079	(0.0350)***	0.1012	-0.0304 (0.0296)	0.1751
3 months late	-0.2079	(0.0350)***	0.1012	-0.0304 (0.0296)	0.1544
4+ months late	-0.5519	(0.0355)***	0.2973	-0.0787 (0.0775)	0.1325
Delinquent	-0.1295	(0.0518)**	0.0627	-0.0081 (0.0102)	0.0459

Bivariate Probit with instruments

Definition	Estimate	Std. Error	ρ	ATE (Std. Error)	Avg. Default
2 months late	-0.2451	(0.0338)***	0.1261	-0.0385 (0.0365)	0.1751
3 months late	-0.2986	(0.0348)***	0.1372	-0.0441 (0.0429)	0.1544
4+ months late	-0.3769	(0.0360)***	0.1836	-0.0519 (0.0517)	0.1325
Delinquent	did not converge!				0.0459

Notes: Estimates signify the coefficients of GroupAffiliation for increasing thresholds of loan default. ρ is the correlation of the error terms and ATE the average treatment effect.

5.6 Heterogeneity in the Group Effect

With confidence in the robustness of our results, we now come to the discussion of our findings. While we verified *Hypothesis 1*, that GroupAffiliation has a negative impact on loan default, we seek to explain the surprising finding that borrowers with worse observed and unobserved characteristics select into group loans, although we hypothesized that the group leader's monetary and reputational incentives should lead to a negative selection into this contract type (*Hypothesis 4*). To give reasoning to our observations, we first test *Hypothesis 2* and *Hypothesis 3* that signals work for lenders in that they represent valid information.

In a single-equation probit model of loan default (Table 9, first model), we find that neither the fraction of the loan amount financed by the group leader (GLCol) nor the interaction term of an overperforming group rating and the number of billed payments in the borrower's group (GroupRatingBinOverperf:NoBilled) have a significant impact on repayment performance. That is, the group leader's signals are not useful for lenders.[11]

[11]Even when dichotomizing the variables GLCol and GroupRatingBinOverperforming or interacting

Table 9: Probit of Loan Default for Group Loans only

	without GroupGrowth		with GroupGrowth	
	Estimate	Std. Error	Estimate	Std. Error
(Intercept)	-2.3850	(0.1981)***	-2.3870	(0.1986)***
CreditGrade A	0.4765	(0.1833)**	0.4783	(0.1838)**
CreditGrade B	0.6002	(0.1725)***	0.5934	(0.1730)***
CreditGrade C	0.8524	(0.1655)***	0.8337	(0.1659)***
CreditGrade D	1.0640	(0.1664)***	1.0410	(0.1668)***
CreditGrade E	1.4020	(0.1711)***	1.3690	(0.1717)***
CreditGrade HR	1.8510	(0.1711)***	1.8000	(0.1718)***
CreditGrade NC	2.1320	(0.2893)***	2.0600	(0.2902)***
DebtToIncomeRatio	0.0328	(0.0150)*	0.0339	(0.0151)*
DelinquenciesLast7Years	0.0028	(0.0014)*	0.0027	(0.0014).
InquiriesLast6Months	0.0260	(0.0041)***	0.0262	(0.0041)***
TotalCreditLines	-0.0006	(0.0017)	-0.0007	(0.0017)
IsBorrowerHomeowner True	-0.0004	(0.0495)	0.0048	(0.0496)
LengthStatusMonths	-0.0008	(0.0004).	-0.0008	(0.0004)*
AmountBorrowed	0.0000	(0.0000)***	0.0000	(0.0000)***
Income NotDisplayed	-0.2568	(0.2705)	-0.3011	(0.2721)
Income NotEmployed	3.8110	(48.790)	3.7320	(49.050)
Income $25-49k	-0.0206	(0.0921)	-0.0255	(0.0921)
Income $50-74k	-0.1113	(0.1030)	-0.1103	(0.1030)
Income $75-99k	-0.1279	(0.1282)	-0.1228	(0.1283)
Income $100k+	-0.0288	(0.1364)	-0.0239	(0.1366)
EmploymentStatus Not available	0.1661	(0.2673)	0.1676	(0.2690)
EmploymentStatus Not employed	-3.4430	(48.790)	-3.4060	(49.050)
EmploymentStatus Part-time	-0.0537	(0.1683)	-0.0522	(0.1685)
EmploymentStatus Retired	-0.0348	(0.2191)	-0.0270	(0.2184)
EmploymentStatus Self-employed	0.1018	(0.1048)	0.0994	(0.1049)
FundingOption Open For Duration	-0.1781	(0.0470)***	-0.2052	(0.0475)***
Endorsements	-0.1151	(0.0462)*	-0.0775	(0.0471)
BorrowerCity	-0.0660	(0.0428)	-0.0614	(0.0430)
GroupCol	-1.6280	(0.6231)**	-1.6240	(0.6324)*
GLCol	-0.0634	(0.1505)	-0.0695	(0.1506)
StateDiffGL Same	-0.2157	(0.0714)**	-0.1940	(0.0717)**
GLRewardPercentageOfBase	0.2641	(0.0776)***	0.1850	(0.0794)*
GroupGrowth	NO		0.0036	(0.0007)***
GroupRatingBinOverperf:NoBilled	0.0000	(0.0001)	-0.0005	(0.0001)**
GroupRatingBinUnderperf:NoBilled	-0.0001	(0.0001)	-0.0001	(0.0001)
Observations	6,378		6,378	
AIC	4,704.9		4,727.4	

Notes: Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

To give a possible explanation for these results, we recall the group leader's incentive design. The group leader's incentives are conflictive as well as his functions. On the one hand he is supposed to filter applying borrowers for credibility and is rewarded a payment reward upon successful loan repayment. This is what we referred to as long term incentives. On the other hand, applying borrowers seek to get their listing funded with his group and this may induce him to excessively accept their applications and endorse their listings because he is rewarded a match reward for every arranged loan (short term incentive). The design of this incentive mechanism seems to play a crucial role in determining the group leader's actions. A look at the coefficient of the GLRewardPercentageOfBase[12] reveals a significant positive impact of the rewards on loan default. This hints at a dominant short term effect of the reward design, because group leaders that choose to be paid for their efforts seem to put more effort in getting their members' listings funded than in diligent screening.

This provides a potential explanation for the failure of a group leader's participating bid and the group rating to signal information and loan quality. We will discuss this issue in detail below. We first consider the insignificant estimate of the group leader's participating bid that is even more surprising, given that group members are very well able to discriminate between defaulting and non defaulting loans (see GroupCol in Table 9), though they have less information about the borrower.[13] Then we will turn to the more complex issue of the group rating system.

As already mentioned in the theory section, group leaders used to start the auction with their bid at an exorbitant maximum rate to initiate herding behaviour of other market participants that finally bid them out of the auction. Following this line of argumentation, the group leader's participating bid could be a remnant of the group leader's first bid strategy. A poor quality loan that didn't even induce the desired herding behaviour after the group leader's first bid will finally – if at all – be financed by the group leader himself. This seems to be a possible explanation for our rejection of *Hypothesis 2*, though further research into the auction process will help to shed more light on this issue.[14]

them with other variables, we find that they have no significant effect on loan default.

[12]This is the fraction of the match and payment reward the group leader claims for himself.

[13]One could object that new borrowers are primarily recruited by other groupmembers, which may be better informed about the borrower's characteristics. We would however argue, that the recruiting process is primarily driven by the group leader, because there is no financial incentive for a group member to recruit new borrowers and these incentives turn out to be important when we look at the recruiting process of groups – in the form of the number of loans funded – before the reward system was discontinued on September 12th, 2007 and thereafter (Table 1).

[14]We do not go into details regarding a possible collusion of borrower and group leader though these

Interestingly, the group rating turns out to be a very good predictor of loan default if and only if we control for GroupGrowth (confer Table 9, second model). Figure 2 further shows at the example of the largest group, that groups are growing fast as long as they are rated overperforming.[15] We also see in Table 9 that loans with high GroupGrowth are performing poor. If we put this together, then an overperforming rating per se leads to a lower loan default. But this effect is counteracted by the opposed effect that an overperforming rating induces a group leader to grow his group – probably induced by the short term reward structure – and GroupGrowth is associated with a higher probability of loan default – maybe because the group leader has a maximal capacity of diligent screening and monitoring. This argumentation leads to a justified rejection of *Hypothesis 3*. An overperforming rating does not reduce the probability of a loan to default, because of a non-functioning reputation system that is driven by short term incentives.

Table 10: Correlation Matrix of Group Characteristics

	StatusBin	GLRewardPercentage	GroupGrowth	GroupRatingOver:NoBilled	GroupRatingUnder:NoBilled	GroupRatingNone	StateDiffGLSame	GroupCol
GLRewardPercentage	0.05							
GroupGrowth	0.08	0.2						
GroupRatingOverperf:NoBilled	-0.03	0.05	0.63					
GroupRatingUnderperf:NoBilled	-0.03	0	-0.08	-0.15				
GroupRatingBinNone	0.03	-0.04	-0.34	-0.35	-0.16			
StateDiffGLSame	-0.05	-0.06	-0.13	-0.08	-0.07	0.16		
GroupCol	-0.03	-0.08	-0.01	0.04	-0.01	0	0.03	
GLCol	0.04	-0.02	-0.05	-0.11	-0.05	0.23	0.05	0.07

conventions can not be ruled out. It may for example be interesting to look at the bid number of the group leader's bid to deduce particular strategies and patterns.

[15]See also the positive correlation of 0.63 between GroupGrowth and the interaction term GroupRatingBinOverperforming:NoBilled in the correlation matrix (Table 10).

The rejection of *Hypotheses 2* and *3* leads to one possible explanation for the positive self-selection into group loans. The dominant short-term incentives induce group leaders to select borrowers without diligent screening and we may therefore find a positive self selection into groups. However, the same reasoning holds if we assume that group leaders just have a limited capacity of diligent monitoring. We give another explanation for the positive selection effect, when we address the selection into sample in the methodological shortcomings.

5.7 Methodological Shortcomings

There are three obvious methodological shortcomings that we wish to address before we conclude.

First, we did not test the probit of loan default for group loans in Table 9 for selectivity bias. Though we explicitly focussed on the effect of GroupAffiliation in this paper, it is reasonable to assume that other variables of the borrower's contract choice are also endogenous and therefore biased our estimates. For example it is very likely that borrowers with worse observed and unobserved characteristics select into paid groups. Fast growing groups may be more likely to select worse borrowers because group leaders can not invest much time into diligent screening of their borrowers. To control for this selectivity would require at least one instrumental variable for every possibly endogenous covariate. Otherwise the test for endogeneity crucially hinges on the assumptions that all other variables are exogenous.

Second, a severe problem of our analysis, also concerning selectivity bias, is the selection into sample. While we control for the borrower's selection into treatment, we did not address the previous source of possible selectivity bias. To make this point clear, imagine lenders have particular assumptions about the role of groups in reducing default risk. These assumptions may be driven by the recent (publicity) success of group lending programs by the Grameen Bank in Bangladesh or the marketplace's public announcements that "successful groups have a lower default rate". These assumptions may lead lenders to bid on group listings they would not bid on if it were individual listings. Or assume group leaders, whose job it is to support borrowers to get their listing funded, just help borrowers to write more attractive and sophisticated listings. Both arguments follows a selection of group borrowers with worse observable and unobservable characteristics into the sample. Ignoring this bias and treating the selection process into the sample as a purely random phenomenon (as we did) would systematically bias the effect of group affiliation on loan default upwards. This will have distinct consequences for the validity of our estimates. However we argue, not for the validity of the rejection of our *Hypothesis 1*. Instead, our (negative) estimate of the group affiliation effect on loan default can be interpreted as a lower bound estimate. Factoring in the possible positive selection into sample will only correct the group affiliation dummy further downwards.

A more appropriate solution to this problem would be to estimate a trivariate probit model of the following form, using numerical integration or simulation techniques.

$$\begin{aligned} G_i^* &= Z_{1i}\gamma_1 + v_{1i} && (6) \\ S_i^* &= Z_{2i}\gamma_2 + G_i\gamma_3 + v_{2i} && (7) \\ Y_i^* &= X_i\beta + G_i\delta + S_i\eta + u_i, && (8) \end{aligned}$$

where Equations (6) and (8) are the well known bivariate probit equations and the additional dummy regressor S_i in the structural equation indicates if listing i got funded and is therefore observed in the sample. S_i^* is the corresponding latent variable and S_i is the dycotomous variable, indicating the selection into the sample and following the rule

$$\begin{cases} S_i = 1 & \text{if } S_i^* > 0 \\ S_i = 0 & \text{if } S_i^* \leq 0, \end{cases}$$

that is a loan is funded if there is a sufficient number of lenders for which the expected net benefits of financing this loan is positive. The lenders' decision to fund a loan is modelled in Equation (7) as dependent on controls Z_{2i} and group affiliation G_i. The error terms are assumed to be independently and identical distributed as trivariate normal:

$$\begin{pmatrix} v_{1i} \\ v_{2i} \\ u_i \end{pmatrix} \sim i.i.d.N\left(\begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & \rho_{12} & \rho_{13} \\ \rho_{21} & 1 & \rho_{23} \\ \rho_{31} & \rho_{32} & 1 \end{bmatrix} \right).$$

This model can be evaluated referring to the GHK simulated maximum likelihood estimator, which is available in the statistical program package STATA (*mvprobit*, see Cappellari and Jenkins 2003) or approximated using a Heckman two-stage procedure described in Arendt and Holm (2006). The validity of our estimates crucially hinges on the assumption that $\rho_{2\cdot} = \rho_{\cdot 2} = 0$.

Third and finally, we did not consider a problem that follows the same reasoning as the one discussed above, but requires a different statistical solution. Assume that lenders may be willing to charge a lower interest rate for group borrowers than for individual listings. If that was the case, our estimates of the GroupAffiliation effect on loan default would be too optimistic. A more appropriate model for this case would be a simple Heckman two-stage model with a probit selection and an OLS outcome equation on a loan's realized return on investment.

6 Conclusion

This paper makes important contributions to the literature on financial intermediation in online markets. We examine the role of reputation based intermediaries in online peer to peer lending platforms. We show that the group lending concept employed by the online market has certain similarities with group lending programs based on joint liability in the developing world. In our analysis, we abstract from these attributes and solely focus on the function of groups as intermediaries, first discussed in Prescott (1997).

In line with the theory of financial intermediation, we find that these intermediaries significantly reduce credit risk in the form of loan default on the platform. This effect is however counteracted by a positive selection of borrowers into group contracts. That is, borrowers with *worse* observable and unobservable characteristics select into group rather than individual loans. We provide evidence that this is due to a missleading group reputation system that is driven by a short term incentive design, which was introduced by the platform to expand the market and has been discontinued in September 2007. We show that these short term incentives induced group leaders to set wrong signals that lead in turn to an adverse selection problem in the market for group loans.

We argue, that the group system could have provided a substantial contribution to mitigate prevalent informational asymmetries in the market. However, the match reward that succeeded in growing the market, counteracted the incentives for sustainable group growth at the expense of less diligent screening and monitoring, and higher default rates. The discontinuation of the group leader rewards in September 2007 effectively choked off the group system and thereby leaves a promising way to control credit risk in the market untapped. Since September 2007, only 33 active groups have been founded – compared to 707 in the same time period before. Not surprisingly, the fraction of groups that no longer accepts new borrowers makes up 39 percent of the groups that ever had a loan and the fraction of grouploans is negligible (see Figure 1). As it stands, the group system is no longer of use for the market and for economists, using the platform as an excellent petri dish to test their models.

References

Abbink, K., Irlenbusch, B., and Renner, E. (2006). Group Size and Social Ties in Microfinance Institutions. *Economic Inquiry*, 44(4):614–628.

Akerlof, G. (1970). The Market for Lemons: Qualitative Uncertainty and the Market Mechanism. *Quarterly Journal of Economics*, 84(3):488–500.

Angrist, J. D. (1991). Instrumental Variables Estimation of Average Treatment Effects in Econometrics and Epidemiology. Technical Working Paper 115, National Bureau of Economic Research.

Arendt, J. N. and Holm, A. (2006). Probit Models with Binary Endogenous Regressors. Discussion paper, University of Southern Denmark.

Avery, R., Bostic, R., Calem, P., and Canner, G. (1996). Credit Risk, Credit Scoring, and the Performance of Home Mortgages. *Federal Reserve Bulletin*, 82:621–648.

Banerjee, A., Besley, T., and Guinnane, T. (1994). Thy Neighbor's Keeper: The Design of a Credit Cooperative with Theory and a Test. *Quarterly Journal of Economics*, 109(2):491–515.

Becker, G. S. (1973). A Theory of Marriage: Part I. *Journal of Political Economy*, 81:813–834.

Berger, S. and Gleisner, F. (2008). Emergence of Financial Intermediaries on Electronic Markets: The Case of Online P2P Lending. Working paper, University of Frankfurt.

Besley, T. and Coate, S. (1995). Group Lending, Repayment Incentives and Social Collateral. *Journal of Development Economics*, 46(1):1–18.

Bhattacharya, S. and Chiesa, G. (1995). Proprietary Information, Financial Intermediation, and Research Incentives. *Journal of Financial Intermediation*, 4(4):328–357.

Bikhchandani, S. and Sharma, S. (2001). Herd Behavior in Financial Markets. *IMF Staff Papers*, 47:279–310.

Bond, P. and Townsend, R. (1996). Formal and Informal Financing in a Chicago Ethnic Neighborhood. *Economic Perspectives*, 20(4):3–27.

Breuer, W. (1995). Finanzintermediation und Reputationseffekte. *Kredit und Kapital*, 4:516–534.

Cappellari, L. and Jenkins, S. (2003). Multivariate Probit Regression Using Simulated Maximum Likelihood. *The Stata Journal*, 3(3):278–294.

Chircu, A. and Kauffman, R. (2000). Reintermediation Strategies in Business-to-Business Electronic Commerce. *International Journal of Electronic Commerce*, 4(4):7–42.

Diamond, D. (1984). Financial Intermediation and Delegated Monitoring. *Review of Economic Studies*, 51(3):393–414.

Evans, D. and Jovanovic, B. (1989). An Estimated Model of Entrepreneurial Choice under Liquidity Constraints. *The Journal of Political Economy*, 97(4):808–827.

Evans, W. and Schwab, R. (1995). Finishing High School and Starting College: Do Catholic Schools Make a Difference? *Quarterly Journal of Economics*, 110(4):941–974.

Freedman, S. and Jin, G. Z. (2008). Dynamic Learning and Selection: The Early Years. Working paper, University of Maryland.

Gale, D. and Shapley, L. (1962). College Admissions and the Stability of Marriage. *American Mathematical Monthly*, 69(1):9–15.

Ghatak, M. (1999). Group Lending, Local Information and Peer Selection. *Journal of Development Economics*, 60(1):27–50.

Gomez, R. and Santor, E. (2003). Do Peer Group Members Outperform Individual Borrowers? A Test of Peer Group Lending Using Canadian Micro-Credit Data. *Bank of Canada*.

Heckman, J. J. (1978). Dummy Endogenous Variables in a Simultaneous Equation System. *Econometrica*, 46:931–959.

Heng, S., Meyer, T., and Stobbe, A. (2007). Implications of Web 2.0 for Financial Institutions: Be a Driver, Not a Passenger. *Deutsche Bank Research, E-conomics*, 63.

Hermes, N., Lensink, R., and Mehrteab, H. (2005). Peer Monitoring, Social Ties and Moral Hazard in Group Lending Programs: Evidence from Eritrea. *World Development*, 33(1):149–169.

Karlan, D. (2007). Social Connections and Group Banking. *The Economic Journal*, 117(517):52–84.

Klein, D. (1992). Promise Keeping in the Great Society: A Model of Credit Information Sharing. *Economics & Politics*, 4(2):117–136.

Klemperer, P. (2004). *Auctions: Theory and Practice*. Princeton University Press.

Leland, H. and Pyle, D. (1977). Informational Asymmetries, Financial Structure, and Financial Intermediation. *Journal of Finance*, 32(2):371–387.

MacLeod, W. B. (2007). Reputations, Relationships, and Contract Enforcement. *Journal of Economic Literature*, 45(3):595–628.

Maddala, G. (1983). *Limited Dependent and Qualitative Variables in Econometrics*. Cambridge University Press: Cambridge.

Prescott, E. S. (1997). Group Lending and Financial Intermediation: An Example. *Federal Reserve Bank of Richmond Economic Quarterly*, 83(4):23–48.

Rivers, D. and Vuong, Q. (1988). Limited Information Estimators and Exogeneity Tests for Simultaneous Probit Models. *Journal of Econometrics*, 39(3):347–366.

Rosenbaum, P. and Rubin, D. (1983). The Central Role of the Propensity Score in Observational Studies for Causal Effects. *Biometrika*, 70(1):41–55.

Rothschild, M. and Stiglitz, J. (1976). Equilibrium in Competitive Insurance Markets: An Essay on the Economics of Imperfect Information. *Quarterly Journal of Economics*, 90(4):629–649.

Smith, J. and Todd, P. (2001). Reconciling Conflicting Evidence on the Performance of Propensity-Score Matching Methods. *American Economic Review*, 91(2):112–118.

Sobel, J. (2002). Can We Trust Social Capital? *Journal of Economic Literature*, 40(1):139–154.

Sobel, J. (2006). For Better or Forever: Formal versus Informal Enforcement. *Journal of Labor Economics*, 24(2):271–297.

Sørensen, M. (2007). How Smart Is Smart Money? A Two-Sided Matching Model of Venture Capital. *The Journal of Finance*, 62(6):2725–2762.

Spence, M. (1973). Job Market Signaling. *Quarterly Journal of Economics*, 87(3):355–374.

Stiglitz, J. (1990). Peer Monitoring and Credit Markets. *The World Bank Economic Review*, 4(3):351–366.

Stiglitz, J. and Weiss, A. (1981). Credit Rationing in Markets with Imperfect Information. *American Economic Review*, 71(3):393–410.

Tidwell, L. and Walther, J. (2002). Computer-Mediated Communication Effects on Disclosure, Impressions, and Interpersonal Evaluations: Getting to Know One Another a Bit at a Time. *Human Communication Research*, 28(3):317–348.

Tirole, J. (1996). A Theory of Collective Reputations (with applications to the persistence of corruption and to firm quality). *Review of Economic Studies*, 63:1–22.

Varian, H. (1990). Monitoring Agents with Other Agents. *Journal of Institutional and Theoretical Economics*, 146(1):153–174.

Watson, J. (1999). Starting Small and Renegotiation. *Journal of Economic Theory*, 85(1):52–90.

Wilde, J. (2000). Identification of Multiple Equation Probit Models with Endogenous Dummy Regressors. *Economics Letters*, 69(3):309–312.

Wooldridge, J. (2002). *Econometric Analysis of Cross Section and Panel Data*. MIT Press.

Zeldes, S. (1989). Consumption and Liquidity Constraints: An Empirical Investigation. *The Journal of Political Economy*, 97(2):305–346.

Appendix: The Lending Mechanism of Prosper.com

The electronic marketplace is an online auction website where individuals can buy loans and request to borrow money. Borrowers set the maximum interest rate they wish to pay, lenders, bid on specific loans by committing a portion of the principal and setting the minimum interest rate they wish to receive on a particular loan. The online market manages the reverse dutch auction, assembling bids with the lowest interest rates in order to fund the loan.

The company verifies selected borrowers' identity and personal data before funding loans and manages loan repayment. All loans are made by WebBank, a Utah-chartered Industrial Bank and sold to winning bidders registered as lenders. Their unsecured loans are fully amortized over three years, with no pre-payment penalty. The lending site generates revenue by collecting a one-time fee on funded loans from borrowers, and assessing an annual loan servicing fee to loan buyers. In case of a late loan, lenders can choose a collection agency, when the loan is at least one month late. If the collection agency can't collect payment from the borrower after four months of delinquency, the loan will be marked as "charge-off", and will be eligible for sale to a debt buyer.

A unique feature of the platform is its group system that is supposed to reduce default rates in overcoming prevalent asymmetries of information on the platform. The group leader acts as intermediary who is delegated to pre-screen potential borrowers and to monitor loan repayment. To set incentives for diligent screening and monitoring, group leaders are rewarded a payment reward upon the borrower's timely repayment of the monthly rate due. In October 2006, the platform introduced a group rating system to set further incentives for group leaders to build up reputation for their group's past conduct.