Friend or Foe? Disentangling a Network of Unregulated and Non-Intermediated Informal Lending

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Abstract

We collect a comprehensive dataset on an online informal lending forum to study access to credit, how lenders learn from experience, and the impact of social media connections on loan terms. The loans in this forum are small, short duration, and high cost to the borrowers. Evidence from this community shows these loans are profitable in aggregate, but very risky individually. Despite informal lending's widespread use and importance for access to liquidity, it is understudied in the literature. It remains unclear what information lenders use to select loans and what determines credit access. We study this marketplace from the point of view of lenders, because for borrowers to have access to credit, lenders must be willing to supply it. Our results indicate lenders with more experience achieve better loan outcomes and provide more lenient loan terms. Additionally, requests are more likely to be converted into a loan when borrowers and lenders have similar online interests. These findings highlight the importance of intermediaries that increase access to credit and reduce cost, and the role of relationships in lending.

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1 Introduction

In the United States, 4.5% of households are unbanked, with the primary reason being "Don't have enough money to meet minimum balance requirements" (FDIC, 2022). The lack of access to credit and considerable liquidity constraints lead these households to search for alternative forms of credit. Informal credit offers an alternative for this population to access the liquidity they need. Informal credit is defined by Karaivanov and Kessler (2018) as loans that rely on personal relationships or social sanctions as means of enforcement. These loans may be credit obtained from family, friends, neighbors, or strangers with no intermediary between lender and borrower. The nature of non-intermediated loans makes them very difficult to collect data that allows for in-depth studies of the informal credit market, despite its widespread use among consumers.

Further emphasizing the need to understand informal credit is the recent shift in peer-to-peer lending platform policies. In recent years, several FinTech firms have entered the market for household lending and created processes that link borrowers and lenders directly. These marketplace lending platforms have continued to grow, and has allowed consumers previously neglected by traditional banks to gain access to credit (De Roure, Pelizzon and Tasca (2016)), while simultaneously offering high returns for lenders (Kraussl, Kraussl, Pollet and Rinne (2022)). However, peer-to-peer lending platforms have begun to shift their business model by shutting out individual investors and instead partnering with banks to originate loans using the banks' underwriting criteria (Evans (2019)), forcing borrowers to find alternative sources of credit.

This paper studies a large, informal, credit market with no intermediary at all. we collect data from an online forum devoted to informal lending. This lending community has no intermediary to link borrower and lenders, and while there are rules to participate in the community, compliance is voluntary. Credit is unsecured and identities or borrowers and lenders cannot be verified with 100% accuracy. Exact loan arrangements are made in private conversations that we cannot observe, but we can observe loan requests and loans granted.

We are able to match loan requests to actual loans made in this market from 2016 to 2021 and obtain detailed information about each loan and request. These loans are high cost and of short duration, most requests follow community rules, and the default rate at a given time on all loans is a maximum of about 15%. There appears to be a strong sense of community and desire to remain a part of the community, as seen through repeated loan requests for many borrowers.

We study access to credit in this marketplace and the lender-borrower relationship through the point of view of the lender. For borrowers to access credit, lenders must be willing to supply it. We have three main findings. First, more experienced lenders get better loan outcomes, with the probability of a loan defaulting decreasing with experience. While the measure of experience is complicated by a wide dispersion of lender activity and endogeneity, we show results hold when changing the experience measure and we utilize an instrumental variable to address endogeneity issues.

Second, we find evidence of more experienced lenders providing more lenient loan terms, improving access to credit. More experienced lenders select loans with lower interest rates, longer maturities, and give more loans. More experienced lenders in this market appear to understand moral hazard risks and are more diversified, allowing them to take on more loans and handle losses.

Lastly, our data also allows us to study how loan outcomes and terms change when borrowers and lenders have more in common with each other. We utilize novel measures of user connection using self-revealed online interests to measure connection. We find that lenders and borrowers who have more in common are more likely to form a loan and have the loan repaid. Lenders of all experience levels use online activity and information about how similar they are to borrowers to make lending decisions and achieve better loan outcomes, but loan terms do not vary with connection level.

Our unique dataset is one of the largest datasets on informal credit collected to date. We are able to study the market dynamics of an informal loan market through the point of view of lenders, showing market participants may learn from lending experience and additional information about borrowers is captured in self-revealed online interests. These findings highlight the importance of banks, intermediaries, and financial markets, all of which bring people together to increases access to credit, and verifies the findings on the importance of relationships in lending (Karolyi (2017)). Users in the market we study would likely benefit from an intermediary to facilitate lending, who could decrease information asymmetry, increase access for all users, strengthen market competition, protect lenders, and reduce costs for borrowers.

The remainder of the paper proceeds as follows. Section 2 reviews the literature on informal lending, peer-to-peer lending, and social connection. In section 3 we describe the loan market, data, and descriptive evidence on the market. In section 4 we measure experience to study how loan outcomes and terms change with experience, and section 5 develops our measures of user connections. Finally, we conclude in section 6.

2 Literature Review

Despite the importance and widespread use of informal loans, it remains understudied in the literature. Much of the literature thus far has focused on informal loan outcomes in developing countries. Karaivanov and Kessler (2018) use data from Thailand to show informal credit is used for small loans and debt enforcement comes from social ties. Banerjee et al. (2015) runs experiments in 6 developing countries to study the impact of micro-credit on low income consumers and finds no reduction in poverty but do find borrower's businesses expand. Additionally, Angelucci et al. (2015) uses experiments in Mexico and find access to informal loans increases borrowing but finds no increases in income for borrowers. Our setting allows us to study informal lending in the US, which is novel in the literature. We also differ by studying borrower access to credit and how lender behavior changes as experience and relationships evolve.

Most applicable to our paper is a study done by Correia et al. (2022) which uses the same data as the current study. They study this marketplace from the point of view of market efficiency and find that loan terms reflect the economic context of borrower and lenders, with loan interest rate and requested amounts increasing after a local Covid-19 lockdown was implemented. Additionally, narratives among participants contain timely information about borrower circumstances and appear to capture real time changes in the challenges borrowers face. They argue that transparency on informal loans in this setting can improve the efficiency of the market and improve access for borrowers while protecting lenders. We expand this study by focusing on loan selection, credit access, and relationships.

A large section of literature has explored the role of marketplace lending and agent behavior in the consumer credit market more broadly. Our setting is a peer-to-peer marketplace lending platform, but is unique due to the lack of an intermediary and regulations. Still, how marketplace lending impacts consumers is relevant to our setting. Berger and Gleisner (2009) find that peer to peer lending helps reduce information asymmetry and improves borrower credit conditions while De Roure et al. (2016) show that peer to peer lending serves consumers neglected by banks with high risk and small loans, but interest rates are similar on a risk adjusted basis. These results run counter to what we find in our setting, the loans borrowers receive often have extremely high interest rates with large information asymmetry between borrower and lender. Our informal marketplace is serving borrowers that are neglected by banks, but the interest rates observed here are much higher than bank loans. The marketplace under consideration in this paper may result in different outcomes than those found in prior literature due to our unique setting.

Agent behavior and loan determinants in marketplace lending has been studied in more traditional peer-to-peer lending platforms as well. Dorfleitner et al. (2016) find that soft information contained in the textual description describing the reason for requesting a loan hardly predicts default probabilities. Herzenstein et al. (2011) find that as the number of identity claims in narratives increases, so does loan funding but loan performance suffers, because these borrowers are less likely to pay back. Borrowers in our setting have a large amount of private information, so textual descriptions are the only way for borrowers to convey information about themselves. On the more positive side, Iyer et al. (2015) find that screening on soft or nonstandard information is relatively more important when evaluating lower-quality borrowers. They find peer lenders achieve 87% of the predictive power of an econometrician who observes all standard financial information about borrowers. Lin et al. (2012) find that consumers on marketplace lending platforms with more online friendships are associated with lower default rates.

We study the access to credit in a novel setting, and extend the literature on agent behavior by studying online social connection. Recently, research on social connection has begun to emerge to study how economic events are impacted by social networks. To this point, much of the literature on connection uses geographic proximity as a proxy for connection, such as Bayer et al. (2021) who measure the likelihood of investing in housing when a neighbor also invests in housing. The research on connection also uses the aggregate Facebook connections between two areas, introduced by Baily et al. (2018) as a measure of social connection. Using this measure, two geographically distant people are assumed to be more connected if, in aggregate, there is a large number of Facebook connections between the two areas. Some studies, such as Fracassi (2017) use shared education networks, previous employers, or professional memberships to measure connection between two individuals. We add to the social connection research by measuring connections between people using their observed mutual interests, where geographic location is irrelevant. Our data allows us to measure connection between individuals through self identified interests, which has been previously impossible due to data limitations. We can measure whether a user's online activity is relevant for lender's lending decisions. Additionally, we can evaluate if a user's online activity is useful for evaluating borrower credit risk for non-intermediated loans. We are able to obtain user activity over our entire sample period, enabling us to measure interests at any given time, and over time.

3 The Online Informal Credit Market

The informal credit community we study has 128 thousand users, and has the sole purpose of providing a platform for informal loan exchange. In order to be a member of this community, a user's account used must be more than 90 days old, and active in other channels on the website. Posts requesting a loan are not allowed to be deleted, which maintains credit history, and each user can only post once every 24 hours.

The process of obtaining a loan is as follows. A potential borrower posts on the forum asking for a loan, typically listing the amount of money requested, promised repayment amount, repayment date, their location, and a short description of why they need the money. This post requesting a loan has strict formatting requirements, which allows the community to have a bot auto check posts. This bot will automatically delete requests that do not meet the formatting requirements and requests made by users who do not satisfy the membership standards. Additionally, this bot is able to maintain a request and repayment history for every user on the forum, helping to increase transparency in requests. Importantly for us, the strict rules on post formatting allows us to collect the data and parse the needed loan information systematically. An example of a typical loan request on the forum is shown in Figure 1. After a loan request is made, a potential lender will then see the post requesting a loan, and message the potential borrower. The lender can ask for any information they deem necessary to vet the borrower, while the borrower is free to choose what information they give or don't give to the lender. The two parties negotiate privately, and if they agree to a loan, the lender will make a post on the forum stating they gave a loan to the borrower in the required format. Finally, once a loan is due, the lender will return to the forum to report whether the borrower repaid the loan or not. The strict formatting required for all steps of the loan process, along with the auto moderation bot cleaning up improper postings, allows us to collect data on every part of the loan process, and track the performance of a loan through its life.

While the negotiation process between borrower and lender is done in private, there is no reason to believe the lender would offer to receive less in repayment than offered in the loan request. Likewise, there is no reason for lenders to allow borrowers to repay less than previously arranged. If anything, a borrower may agree to repay more than they initially stated after negotiating with a lender. For these reasons, the posts we observe are a good measure of the credit activity in this marketplace.

In this market, there is no incentive for compliance with the rules other than user reputation and ability to access credit via the community in the future. The only known enforcement action that can be taken is banning a user from the community, and since loans do not have any collateral, a loss of 100% is assumed in the case of default. While the loans are generally short term and of small amounts, in aggregate this is a large marketplace with repeated users. We document about 95,000 loans, worth about 26 million USD originated in this market from 2016 to the end of 2021. These loans were between about 3,000 unique lenders and 15,000 unique borrowers. There is a very clear dynamic of repeated lending and borrowing, which makes reputation important and relies on members of the community to follow the rules.

Data

We collect all posts from this community, and filter for all loan requests. For each request, we collect the username of the user requesting the loan, the date of the request, the requested amount, the poster's location, the promised repayment amount, the promised repayment date, the system that is used to transfer money (Paypal, Venmo, etc), and the text of the request which may contain a short narrative about why the money is needed.

We are also able to access a database that stores all loans originated in the market. From this database, we can extract the username of the borrower and lender, the amount lent, the date of the loan, and whether a loan was marked as paid or unpaid. We are able to merge the requests and loans on a unique loan ID.

Our dataset contains 168,317 loan requests for the period 2016-2021. Out of these requests, 111,670 are not removed due to the violation of community rules, out of which 51,319 requests have complete information on loan amount, promised repayment amount, and promised maturity, allowing us to compute an interest rate on the loan. We remove 299 requests that erroneously took the year as repayment amount to get 51,020 requests. For our loan database, we have information on 95,381 loans, out of which we can merge 77,545 to a request, for a raw merge rate of slightly higher than 80%. Out of these, we are able to price 36,638 loans. If a loan is missing data on requested amount, promised repayment amount or repayment date, we cannot calculate an interest rate. We only study loans that we are able to price so that we can measure performance of the market as a whole, and changes in terms over time.

A small complication is that 8,336 of these loans were repeated transactions where the same borrower and lender agreed to multiple different loans over a period of time. These loans require some adjustments to capture the correct loaned amount and loan origination date. However, due to the nature of the data, we must assume the same maturity length and same interest rate as the first loan between a borrower and lender in order to obtain a promised repayment amount. Analysis on lender experience and relationships will be done excluding these loans since they were not available for all lenders to choose. Excluding these loans changes the magnitude of loan profitability, but not the conclusions reached.

An important note is that we cannot observe the true default rate in this market. When a loan defaults, a lender is supposed to mark a loan as paid or unpaid. However, since there is no incentive for rule compliance, we do see that lenders do not always mark whether a loan results in repayment or default. Due to this, we have about 11% of our matched loans with no data on whether a loan defaulted or was repaid. To overcome this, we calculate an upper and lower bound of default of our loans. The lower bound is defined as the percentage of loans marked as unpaid by the lender. We know this is the lower bound because we know for sure at least those loans were unpaid, but more could have been unpaid. The upper bound of default is one minus the percentage of loans marked as paid. All the loans not marked as paid could potentially be unpaid loans, however some of the loans could have been repaid and not marked as such by the lender. An example of this process is illustrated in Table 1. We assume if a loan was marked as paid, it was actually paid, and if a loan was marked as unpaid, it was actually unpaid. The table shows for a given month, 86% of loans were marked as paid, and 4% of loans were marked as unpaid. This leaves 10% of loans in the month with an unknown result. As an upper bound of default, we can assume all 10% of unmarked loans were unpaid. As a lower bound of default, we can assume all 10% of unmarked loans were repaid. Of course, neither of these are the true default rate, but this does give us a tight, steady, and consistent default range throughout our sample. Figure 2 plots the upper and lower bounds of default over and sample and shows that these bounds generally move together, and the spread between them is small. The difference between the average default rate in the upper bound and the average default rate in the lower bound is about 6%. The default rate is very low considering the lack of consequences that result from defaulting on a loan. This highlights the potential importance of community and desire to remain a member in this market.

Finally, for all loans we are able to calculate the actual repayment date, the process of calculating actual repayment date is as follows. If the date a loan is marked unpaid is available, we take the earlier of the unpaid date and the promised repaid date. If repaid date is empty and unpaid date is also empty, we have to take the promised repaid date as actual repayment date. Lastly, if repaid date is marked, we take the repaid date as the actual repayment date. This process revealed 1,572 instances where the actual repayment date was the same as the loan origination date. This is due to data entry error, and we drop these loans as we cannot obtain an interest rate on them. This brings our sample to 35,066 loans we can accurately price with promised repayment date and actual repayment date.

These loans occur between 1,962 unique lenders and 8,544 unique borrowers, totaling more than 7.5 million dollars in informal credit. Compared to the entire population of loans originated, our sample is able to capture 65% of the unique lenders, 56% of the unique borrowers, and 30% of total value of loans.

For use interests, we are able to collect the activity history in other communities on the website for all users who have ever given or requested a loan in this forum. This allows us to connect users together through shared interests to study how connection may matter for loan terms and outcomes. An illustrative example of how a lender may be connected to all borrowers who request a loan on a day is show in Figure 3. A line represents the borrower is connected through mutual revealed interests to the lender, with the thickness of the line illustrating the intensity of the connection.

Descriptive Evidence

In Table 2, we report summary statistics for loan requests and loans. Out of 51,020 requests with complete and accurate information, we can find 35,066 corresponding loans. The average amount requested is $273, with the median at $150. The mean and median amount actually loaned is less than the mean and median amount requested, signaling that lenders may not be as willing to grant high dollar value loans. Interestingly, promised maturity is lower than actual maturity, which provides evidence of late payments. Finally, loans have a slightly higher average and median interest rate than requests, indicating lenders choosing to give loans that are most profitable to them. The promised interest rate is winsorized at the 10% level.

Table 3 shows loan summary statistics broken down by year. Overall, average loan size and median interest rate have increased over time, but the median maturity of a loan has stayed relatively constant. Of note, in 2019 we see a large spike in the number of loans in our sample. This is due to the community enforcing stricter rules on loan requests, allowing us to successfully parse more loans in beginning in 2019. Figure 4 shows the median interest rate on loans for maturity ranges, which exhibits an inverted shape, usually associated with times when financial distress is ahead.

4 Lender Experience

To understand borrower's access to credit in the informal marketplace, we must understand how lenders behave when evaluating potential loans. We begin by evaluating loan terms in the market as a whole, then look at how individual lenders loan choices evolve as they gain experience giving loans.

To evaluate what factors may be important for a request becoming a loan, we present results from a logit regression in Table 4, where the dependent variable is one if a loan request was made into an actual loan. We use our 51,020 requests and drop 7,532 prearranged loans to get 43,488 requests. Maturity is the length of a loan, requested amount is the amount a potential borrower asks for, and promised repay amount is the amount to be repaid. In USA is a dummy equalling one if the request was for a borrower in the USA, this is used to evaluate if lenders prefer US based borrowers. Payment used is a dummy equalling one if the payment system was Paypal, Venmo, Cashapp, or Zelle, which are the most common payment systems used and may be more preferred by lenders. Never Defaulted is a dummy equalling one if a borrower has repaid all previous loans. This dummy variable must be used instead of the actual default rate of a borrower because first time borrowers will have a default rate of zero, artificially inflating the likelihood of getting a loan due to default rate. Loans Outstanding is how many loans a requestor has outstanding as of the date of the request for a new loan. Number of requests is the number of past requests, filled or not, a requestor has as of the date of the request for a new loan. Default rate, loans outstanding, and prior requests are potential indicators of borrower quality. Loans requested on a day is the number of loans requested on the forum in a day. Weekend dummy equals 1 if the request was made on a weekend. The last two variable are used to reflect lender attention where a request may get overlooked on very active days and weekends.

A few variables are related to textual analysis done on the body of a loan request. Dorfleitner et al. (2016) use length of the text, which we call number of words, to help predict funding probability. Netzer et al. (2019) also uses % of words with more than 6 letters as a complexity factor to predict default, which is % words complex. We also use the SMOG index from McLaughlin (1969) to measure the reading level required to understand a text. Finally, for every year we find the 100 most common words used in requests, excluding stop words. We then count the number of words an individual request has that is included in these 100 words, divide this by the total number of words, and add this variable as Popular Words. These textual analysis variables will help us study the importance of borrower narratives.

We run a regression with these variables on two subsets of the data. One for only first time requestors, and one for requestors with two or more requests. The first time request regression does not use Never Defaulted dummy, Loans Outstanding, or Number of Requests as these will be zero for everyone. Of the 43,488 requests, 16,020 are a first request for a user, while 27,468 are at least the second request for a user. Among the first requests, 5,378 (34%) became a loan. While among the at least a second request for a user pool, 15,237 (55%) became a loan. Overall, 20,615 requests became a loan, and 22,873 did not.

This regression yields sensible results that would be expected of any loan market, higher maturity, more expensive, and lower return requests are less likely to become a loan. Of note, among first time requests, using a more common payment system is more important for obtaining a loan than among repeat requests. Additionally, first time requests are less likely to get a loan when more complex words are used and when more popular words are used as compared to repeat requests, potentially indicating distrust of these requests.

Individual Experience

We now transition from looking at loan terms in aggregate to uncovering how terms and outcomes change as lenders become more experienced in the marketplace. The measurement of experience is difficult as it is endogenous, and depending on the specification of experience, the interpretation or results changes. We initially cannot claim any causal interpretation, because we do not know if lenders learn to get better loan terms and outcomes as they get more experienced, or if some lenders inherently get better terms and outcomes which is what keeps them in the market and gaining experience.

First, we measure experience by forming daily quintiles of lenders experience, where experience is measured as cumulative loans given. We use all loans that we can collect complete data on and are not from a repeated lending relationship, leaving 20,742 loans for this analysis. We drop days that do not have enough loans to form 5 quintiles, resulting in 19,096 loans. Finally, we form a dummy variable for each loan quintile and run the following lender fixed effects linear regression with standard errors clustered by lender:

$$Y_{L,b,i} = \beta_1 1_{Q2,L} + \beta_2 1_{Q3,L} + \beta_3 1_{Q4,L} + \beta_4 1_{Q5,L} + X_{L,b,i} + FE_L + \epsilon \tag{1}$$

Each outcome is between a lender (L) and a borrower (b). Since lenders and borrowers can transact on multiple days, loans are unique for each day (i). $X_{L,b,i}$ represents a series of loan term controls to ensure we are comparing similar loans. Quintile 1 is omitted, so all changes in the outcome are relative to quintile 1. With fixed effects we are measuring how the average lender's loan outcomes change as they move across quintiles of experience, effectively showing how lenders learn.

Results for loan outcomes and terms as lenders move across experience quintiles is shown in Figure 5, with the corresponding table presented in Table A1. As lenders move across quintiles of experience, the likelihood of a loan with an unknown repayment status increases, which is simply a construction of the data. Lenders with more experience will naturally have more unknown loans because there is more opportunity to not mark a loan as paid or unpaid. It also could be more experienced lenders are busier and thus more likely to forget to mark a loan as paid or unpaid. Interestingly, the likelihood of a successful loan is unchanged with experience, and the likelihood of having an unpaid loan decreases with experience. There could be no change in successful loans due to lenders diversifying and taking on more loans, which would result in more defaults but also more repayments. It is also possible that the unknown loans were repaid and the lender is unmotivated to mark a loan as repaid since the transaction is complete and successful.

For loan terms, more experienced lenders take on loans with lower interest rates, longer maturity, and higher principal amounts. More experienced lenders presumably have more capital to give loans and give more loans, so they do not need to interest rate chase. This shows more experienced lenders provide more lenient loan terms, increasing access for borrowers and providing liquidity to the market.

Our analysis of lender experience is made more interesting when we change our experience specification. We now measure experience in an aggregate weekly panel setting to show differences in loan terms and outcomes across experience quintiles. We again form quintiles of experience based on cumulative loans given. However, quintile cutoffs are based on cumulative loans given in the prior week, and the cutoffs are applied to the following week to create rolling weekly quintiles. This rolling measure allows for quintiles to increase when experience increases on average overall, so lenders only move across quintiles if they are gaining experience faster than average. We find the mean outcome of each variable for each week/quintile pair and run the following week fixed effects linear regression with standard errors clustered by week:

$$Y_{w,q} = \beta_1 1_{Q2,w} + \beta_2 1_{Q3,w} + \beta_3 1_{Q4,w} + \beta_4 1_{Q5,w} + X_{w,q} + FE_w \tag{2}$$

$X_{w,q}$ again represents a series of loan term controls to ensure we are comparing similar loans. Quintile 1 is omitted, so all changes in the outcome are relative to quintile 1. With fixed effects we control for changes over time and measure, on average, how lender outcomes in each quintile differ. Thought another way, we are now comparing differences when lenders are endowed with experience.

Results for loan outcomes and terms between quintiles is shown in Figure 6, with the corresponding table shown in Table A2. Contrasting our results from this setting to that found with lender fixed effects, loan terms are very similar, but lenders in the largest quintile are far more likely to have a successful loan and far less likely to have an unsuccessful loan.

The largest lenders see a drop off in the principal of loans given because they give more loans of a smaller amount, shown in Figure 7.

Changes in loan terms match between our two experience specifications, further indicating more experienced lenders provide more lenient loan terms and increase access for borrowers who need liquidity. However, the differences in loan outcomes between our specifications do not match perfectly. In our setting, the average lender, as measured with lender fixed effects, does not exist. We have many lenders who give less than 5 loans total, and about 10 lenders who give hundreds or thousands of loans. An average lender would then be one who gives around 50 loans, which is not common in this market.Table 5 highlights the large profits that can be made in this market, but these profits are only captured by the most active lenders. Figure 10 and Figure 11 further showcase the lack of an average lender in this market. These figures show histograms of lender profitability and number of loans given, respectively. The histograms illustrate how the vast majority of lenders provide less than 5 loans, and profit less than $100 overall. However, there are a few lenders who provide more than 140 loans and profit well over $2,000 overall. This lending distribution highlights how the average lender is a misleading measure of experience in this market.

Comparing Figure 7 to Figure 8 drives home the differences in what each specification of experience measures. Figure 7 uses week fixed effects to compare number of loans given to total amount lent. Lenders with more experience give more loans of smaller amounts than lenders with less experience. Figure 8 uses lender fixed effects to show the same comparison, but this figure measures how a lender learns and changes over time. The largest 10 lenders are extremely active and give many loans, which drives the results seen in Figure 8 and further emphasizes the lack of an average lender in this market.

In both experience specifications, more experienced lenders provide more liquidity at a lower cost to borrowers. At the same time, experience can be hard to gain, individual loans are very risky, and limited information about borrowers is available. This market could benefit from an intermediary that would bring users together to increase competition among lenders and allow more lenders to gain experience, reduce information asymmetry, provide protections for lenders, and reduce costs for borrowers.

Experience Instrumental Variable

In an effort to establish a causal relationship between lender experience and loan terms and outcomes, we develop an IV for experience. The IV is constructed as follows. On any given day, a lender can give a loan to any borrower that posts a request on that day. Our IV for experience is the maximum number of prior loans a lender has given to any borrower who is requesting a loan on a day. If a lender has never given any loans to any borrower requesting a loan on a day, the IV measure is zero. Conversely, if a lender has previously given 3 loans to a borrower requesting a loan on a day, the lender is given an experience measure of 3 for that day, regardless of which borrower the lender ultimately chose to give a loan to.

On a day a lender gives a loan, a borrower requesting a loan the lender has a prior relationship with is exogenous. Having given more loans to any borrower on a day meets the relevance test as it is correlated with cumulative experience. A first stage regression of cumulative loans on our IV results in a coefficient of 62.56 with a t-stat of 103.61. The exclusion restriction of an IV cannot be tested, but we believe it is met. Having given a prior loan to any borrower makes a lender more experienced, and experience can only influence loan outcomes through better selection of requests.

Using our IV, we run a linear regression in the same manner as Equation 1. Our quintiles are now formed from the first stage regression of cumulative loans on our IV, resulting in a predicted cumulative loan value for each loan observation. Results from these regression are shown in Figure 9. Results from the instrumental variable line up well with our initial measures of experience. More experienced lenders give loans with lower interest rates and longer maturities, indicating more lenient loan terms and improved access for borrowers. With experience, a lender is more likely to select a loan that is repaid, showing increasing skill in loan selection.

5 Social Connections

Having shown that loan outcomes and terms change as lenders become more experienced, we can now expand our analysis to ask if loan outcomes and terms change when lenders and borrowers have more in common. We say two users are more connected to each other if they have more overlapping interests. We can identify each user's interests by what other online communities they are active in. Each community in our forum has a specific topic they focus on, such as sports, food, or cars. If a user is active in a community, we say they are interested in that topic, and if two users are interested in the same community we say they are connected. Our measure of connection is novel to the literature and does not rely on geographic location or proxies for interest and connection. We can directly see if users are part of the same community and if they frequently post in the same communities. Users who are members of the same community or post often in the same community have self revealed their interests, allowing us to measure how much two user's interests overlap. Specifically, we ask, do lenders who have more shared interests with a borrower realize better loan outcomes or different loan terms? In other words, are lenders using shared interests to gain additional insights about borrowers?

For every user, we are able to collect every post they ever made in every online community from 2016 through 2021. Using these posts, we can evaluate how similar two users are by measuring how intensely interests overlap. Only connections between borrowers and potential lenders are evaluated. Connections between borrowers or between lenders are not relevant to loan outcomes or lending decisions.

We create two measures of user connection. First, we find the percent of posts in overlapping communities as a percentage of all individual posts for each borrower and lender, and multiply them together to get an aggregate number for each pairing. This measures connection frequency as it shows how often users are posting in the same communities. Next, we find the percent of overlapping communities out of total communities for each borrower and lender, and multiply them together for each pairing. This measures connection intensity as we can see how many communities users have in common.

To begin our analysis, we run a lender fixed effects linear regression in the following form with standard errors clustered by lender:

$$Y_{L,b,i} = \beta_1 Connection + \beta_2 Maturity + \beta_3 Repayment + \beta_4 Requested + FE_L + \epsilon \tag{3}$$

Each outcome is between a lender (L) and a borrower (b) on a specific day (i). Our coefficient of interest is β_1, which will measure how loan outcomes change when lenders and borrowers are more connected through revealed self interests. Our connection measure ranges from 0 to 1, with 0 meaning the users have no overlapping interests and 1 meaning the users mutually share all interests. Table 6 shows regression results for our overlapping posts (frequency) measure. Table 7 shows the results for our overlapping communities (intensity) measure. With both measures, lenders and borrowers who are more connected are more likely to convert a request into a loan, which is also more likely to be successfully repaid. These findings indicate that borrower activity on social media provides additional information that lenders successfully use to screen borrowers and shows relationships in informal lending are important, just as they are in formal lending environments.

We also run, but do not report, the same regression for loan terms and find connection is unrelated to all loan terms. This is what should be expected. Lenders cannot use information about how similar they are to a borrower to determine loan terms. Borrowers propose a loan with their self stated loan terms, lenders see this loan, and can only use revealed borrower interests to decide if they should give a loan. They cannot use connection to change loan terms because loan terms are decided before a lender encounters a borrower.

While there is evidence that lender and borrower connections matter in aggregate, it is also interesting to see the impact of borrower-lender connection relative to all other users.

We approach this similarly to how we measured experience relative to other users. Everyday we form quintiles of connection, where connection is measured as overlapping posts or overlapping communities. We use all loans we can collect data on and are not from a repeated lending relationship. The dataset is expanded to include every loan given and every loan a lender could have given based on users who requested a loan on a day a lender gave a loan. Finally, we drop days that do not have 5 quintiles, resulting in 490,416 loans and loan alternatives. We form dummy variables for each quintile to run the following lender fixed effects linear regression with standard errors clustered by lender:

$$Y_{L,b,i} = \beta_1 1_{Q2,L} + \beta_2 1_{Q3,L} + \beta_3 1_{Q4,L} + \beta_4 1_{Q5,L} + X_{L,b,i} + FE_L + \epsilon \tag{4}$$

Each outcome is between a lender (L) and a borrower (b). Since lenders and borrowers can transact on multiple days, loans are unique for each day (i). $X_{L,b,i}$ represents a series of loan term controls to ensure we are comparing similar loans. Quintile 1 is omitted, so all changes in the outcome are relative to quintile 1. With lender fixed effects, we can measure how loan outcomes change within a lender when they are more or less connected to a borrower.

Results for loan outcomes between quintiles of connection measured by overlapping posts is shown in Figure 12, with the corresponding table shown in Table A3. When lenders become the most connected to a borrower relative to all other connections on a day, they are around 1% more likely to give a loan relative to the least connected users. For intermediate levels of connection, the effect is around 0.5%, but it does not gradually increase as users become more connected. This could indicate users mostly use connection information in their decision making when they are most strongly connected, middle levels of connection do not carry as much meaning. Loan outcomes do show that as users are more relatively connected, they are more likely to have a successfully repaid loan. More connections can mean more avenues are available for a lender to reach a borrower, and a borrower has more social reputation to lose if they do not repay because the borrower and lender are in the same groups.

Results for loan outcomes between quintiles of connection measured by overlapping communities is shown in Figure 13, with the corresponding table shown in Table A4. Our results hold for this alternative measure of connection, the magnitude and trend of a loan existing and a successful loan are nearly the identical to before. Regardless of how we measure connection or whether we measure connection in aggregate or by daily relative lender connection level, we find connection and overlapping interests between borrowers and lenders does matter for loan outcomes. Lenders are able to successfully use activity on social media to screen borrowers, showing relationships and soft information is relevant for lending decisions. Online social media activity provides additional information about borrowers, helping to reduce the information asymmetry present in this marketplace. An intermediary could help reduce this asymmetry and lower search costs to lenders by providing social media activity for all borrowers who request a loan.

Experience and Connection Interaction

So far we have shown that lender experience is important for loan outcomes and terms, and lender connection to borrowers is relevant for loan outcomes and lending decisions. Our final analysis explores how lender experience and connection overlap, and asks if connection information is used more when a lender is less experienced. There are a few possibilities for how experience and connection may work together. One possibility is less experienced lenders do not know how to accurately evaluate borrowers, so they more heavily lean on mutual interests with a borrower to make lending decisions. Experience and connection could also work in tandem where lenders utilize connection information across all experience levels. Finally, experience and connection could be separate forces with no interaction. We utilize our daily quintiles of experience and daily quintiles of connection previously created to assign each loan and potential loan to a daily quintile of lender experience and lender-borrower connection. We analyze how loan outcomes change as a lender moves across quintiles of experience and connection jointly. We do not test how loan terms change because user connection has no impact on loan terms. We run the following linear regression using the number of overlapping posts as our connection measure:

$$Y_{L,b,i} = \alpha + \beta_{k,j}\Sigma_k^5 1_{Qk,exp} * \Sigma_j^5 1_{Qj,conn} + \epsilon \tag{5}$$

Each outcome (Y) is between a lender (L) and borrower (b) on a day (i). All 5 dummies for experience are interacted with all 5 dummies for connection, resulting in 25 interaction effects. The interaction between quintile 1 of experience and quintile 1 of connection is omitted, making all outcomes relative to the least connected and experienced group. Figure 14 shows how the likelihood of a loan existing, a loan being repaid, unpaid, and unknown changes across quintiles. Across each quintile of experience, more connected users are more likely to create a loan and more likely to repay a loan relative to the least experienced lenders and least connected users on a day. For unpaid and unknown loans, there is not much change in the likelihoods across connection quintiles except for the least and most experienced lenders, these two groups of lenders may be over weighting the importance of connection when making lending decisions. Our results hold when using the number of overlapping communities as our connection measure, which means experience of a lender and connection between a lender and borrower pairing work in tandem, where lenders of all experience levels appear to use connection information to give more loans to borrowers with similar interests to themselves, and are rewarded for this with higher success rates on loans.

6 Conclusion

We collect a comprehensive dataset on an online informal lending forum to study credit access through the lens of lender experience and online social connections. The loans we study are small, short duration, and high cost to the borrowers. Despite this, the market is extremely active, with \$26 million in loans from 2016 through 2021 and boasts a very low default rate among borrowers.

Overall, the market behaves as a rational credit market. Evidence suggests lenders with more experience are able to obtain better loan outcomes, provide lower cost loans, and lenders use borrower online activity to gain additional useful information about borrowers. These findings point towards the importance of lender experience for access to credit, and indicate that the under-banked population would benefit from an intermediary to connect them to a lender who is willing to give credit to obtain the liquidity they need. An intermediary would increase access for lenders, decrease information asymmetry, and allow more lenders to give loans. Increased lending competition, coupled with more experienced lenders, will reduce costs faced by borrowers and improve their financial situation.

Our findings clearly show the importance of experience of lenders in this market. While experience can be difficult to measure, differences in experience specification are largely consistent, and differences in results can be explained by the wide dispersion of lender activity. Extremely high profitability is captured by only a few lenders, while the rest of the market sees small gains or losses and gives only a few loans. Introducing an intermediary to this market could equalize this disparity and allow more lenders access to borrowers.

The dynamics of informal credit and the determinants of credit access in this market is important for policy makers to understand due to the large portion of United States households that do not have access to traditional banks or new peer-to-peer lending platforms because of strict lending requirements and larger loan sizes. The current study is one of the first to study informal lending in the United States and focus on loan determinants as opposed to loan outcomes.

References

Angelucci, Manuela, Dean Karlan, and Jonathan Zinmin (2015) "Microcredit Impacts: Evidence from a Randomized Microcredit Program Placement Experiment by Compartamos Banco," *American Economic Journal: Applied Economics*, 7 (1), 151–182.

Baily, Michael, Rachel Cao, Theresa Kuchler, Johannes Stroebel, and Arlene Wong (2018) "Social Connectedness: Measurement, Determinants, and Effects," *Journal of Economic Perspectives*, 32 (3), 259–280.

Banerjee, Abhijit, Dean Karlan, and Jonathan Zinmin (2015) "Six Randomized Evaluations of Microcredit: Introduction and Further Steps," *American Economic Journal: Applied Economics*, 7 (1), 1–21.

Bayer, Patrick, Kyle Mangum, and James W. Roberts (2021) "Speculative Fever: Investor Contagion in the Housing Bubble," *American Economic Review*, 111 (2), 609–651.

Berger, Sven and Fabian Gleisner (2009) "Emergence of Financial Intermediaries in Electronic Markets: The Case of Online P2P Lending," *Business Research*, 2 (1), 39–65.

Correia, Filipe, Antonio Martins, and Anthony Waikel (2022) "Online financing without FinTech: Evidence from online informal loans," *Journal of Economics and Business*, 121.

De Roure, Calebe, Loriana Pelizzon, and Paolo Tasca (2016) "How Does P2P Lending Fit into the Consumer Credit Market?" *Available at SSRN 2756191.*

Dorfleitner, Gregor, Christopher Priberny, Stephanie Schuster, Johannes Stoiber, Martina Weber, Ivan de Castro, and Julia Kammler (2016) "Description-text related soft information in peer-to-peer lending – Evidence from two leading European platforms," *Journal of Banking & Finance*, 64, 169–187.

Evans, Lawrance (2019) "Agencies Should Provide Clarification on Lenders' Use of Alternative Data," *United States Government Accountability Office.*

FDIC (2022) “2021 FDIC National Survey of Unbanked and Underbanked Households.”

Fracassi, Cesare (2017) “Corporate Finance Policies and Social Networks,” *Management Science*, 63 (8), 2420–2438.

Herzenstein, Michal, Scott Sonenshein, Utpal Dholakia, Johannes Stoiber, and Mar Weber (2011) “Tell Me a Good Story and I May Lend You Money: The Role of Narratives in Peer-to-Peer Lending Decisions,” *Journal of Marketing Research*, 48, 138–149.

Iyer, Rajkamal, Asim Ijaz Khwaja, Erzo F.P. Luttmer, and Kelly Shue (2015) “Screening Peers Softly: Inferring the Quality of Small Borrowers,” *Management Science*, 62 (6), 1554–1577.

Karaivanov, Alexander and Anke Kessler (2018) “(Dis)advantages of informal loans – Theory and evidence,” *European Economic Review*, 102, 100–128.

Karolyi, Stephen Adam (2017) “Personal Lending Relationships,” *The Journal of Finance*, 73 (1), 5–49.

Kraussl, Roman, Zsofia Kraussl, Joshua Pollet, and Kalle Rinne (2022) “The Performance of Marketplace Lenders,” *Available at SSRN 3240020.*

Lin, Mingfeng, Prabhala Nagpurnanand, and Siva Viswanathan (2012) “Judging Borrowers by the Company They Keep: Friendship Networks and Information Asymmetry in Online Peer-to-Peer Lending,” *Management Science*, 59 (1), 17–35.

McLaughlin, G.H. (1969) “SMOG Grading - A New Readability Formula,” *The Journal of Reading*, 12 (8), 639–646.

Netzer, Oded, Alain Lemaire, and Michal Herzenstein (2019) “When Words Sweat: Identifying Signals for Loan Default in the Text of Loan Applications,” *Journal of Marketing Research*, 56 (6), 16–83.

Figures and Tables

Figure 1: Example loan request

> Posted by [username] x hours ago
>
> **[REQ] – ($350) (#St Louis, MO, USA), (Repay $400 by 4/22/2022), (PayPal, CashApp)**
>
> Got overzealous with bills and thought I could be all caught up and boy I was very wrong. Thanks

Figure 2: Default Bounds

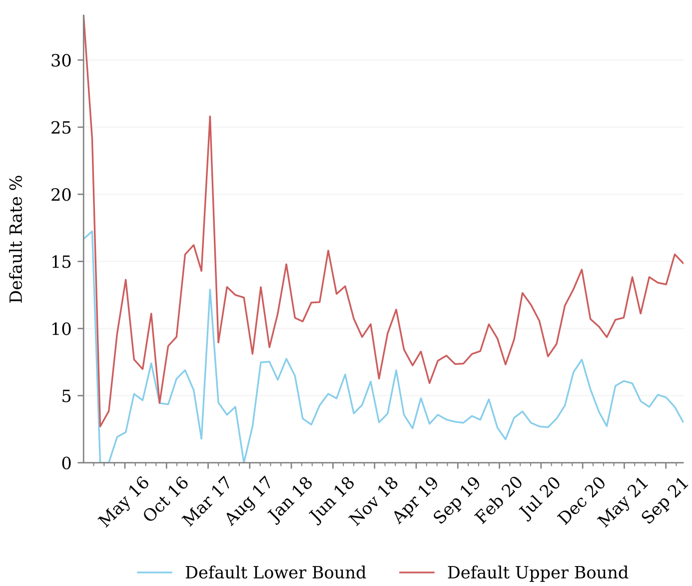


Figure 3: User Connection

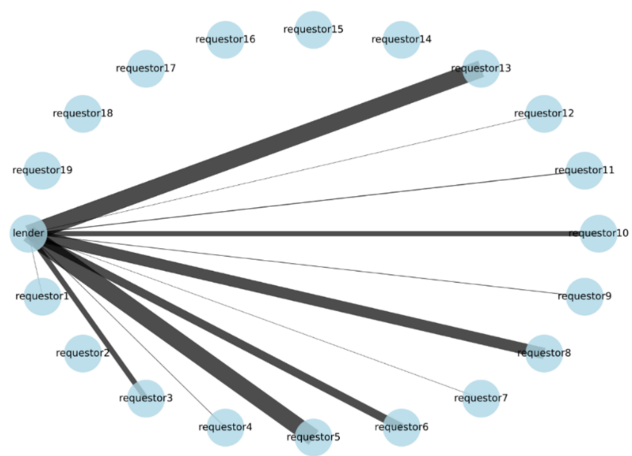


Figure 4: Yield Curve

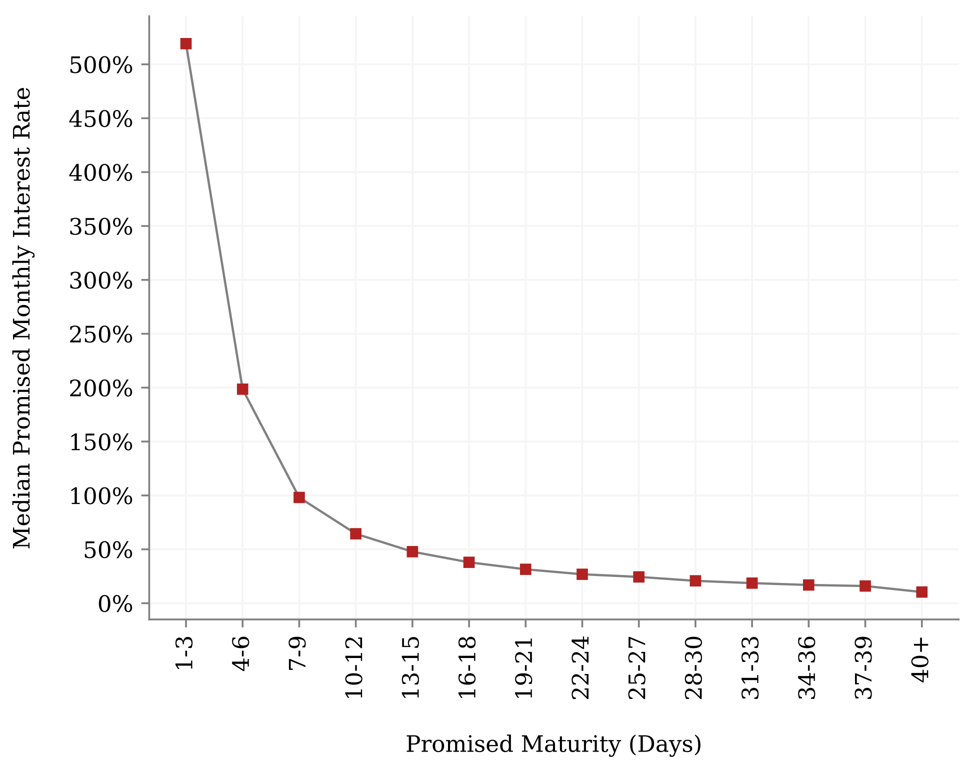


Figure 5: Experience With Lender Fixed Effects

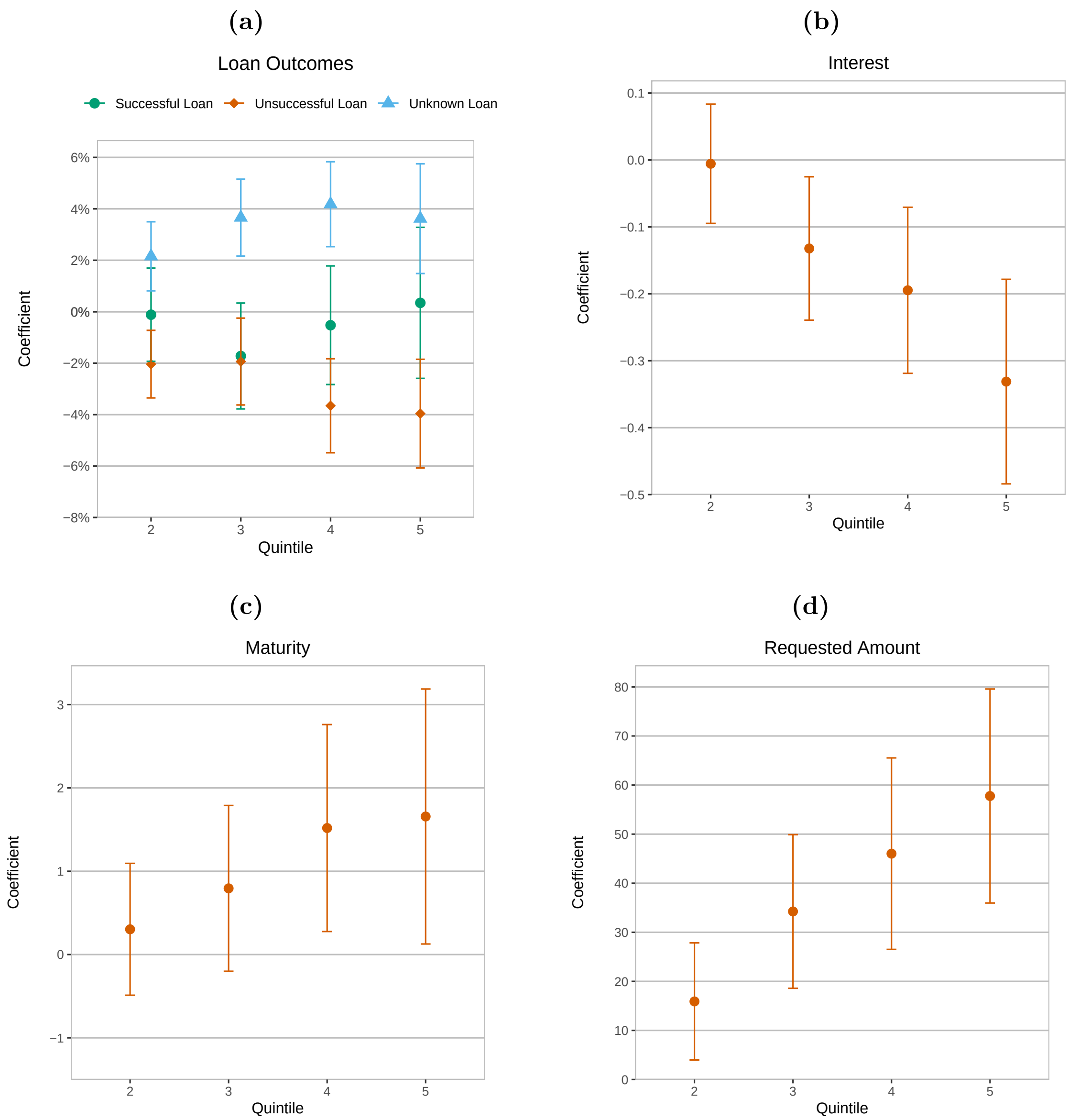
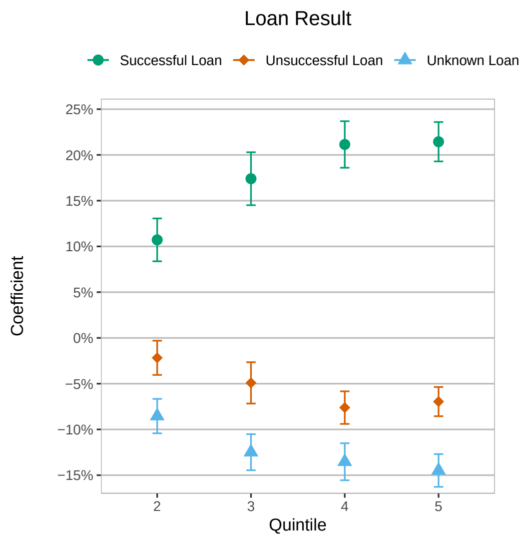
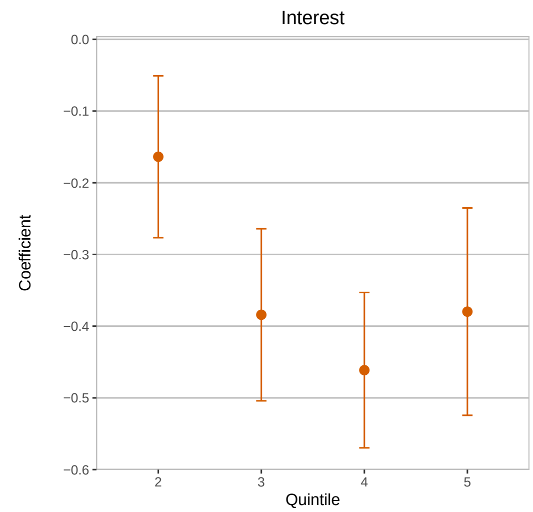


Figure 6: Experience With Week Fixed Effects

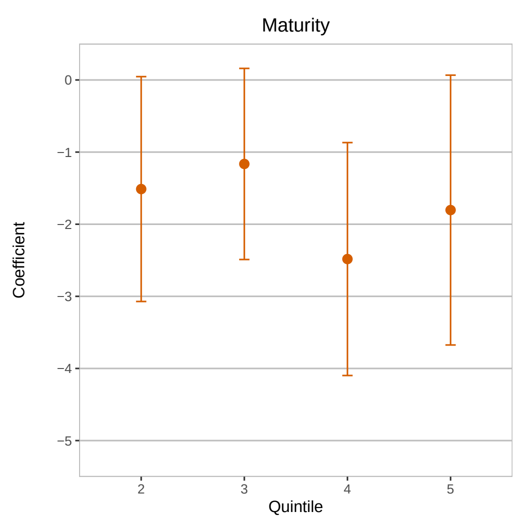
(a)



(b)



(c)



(d)

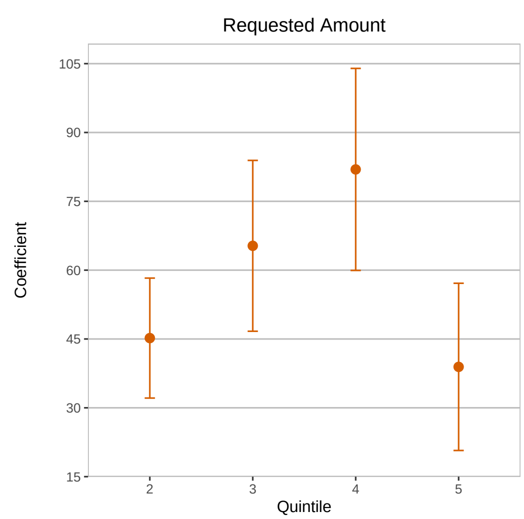
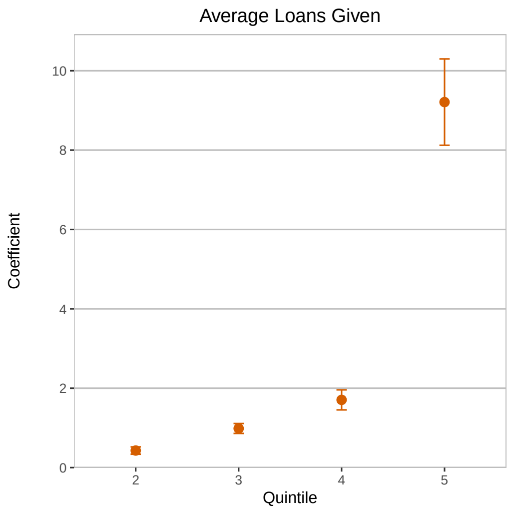


Figure 7: Lender Loans Given vs Amount Given with Week Fixed Effects

(a)



(b)

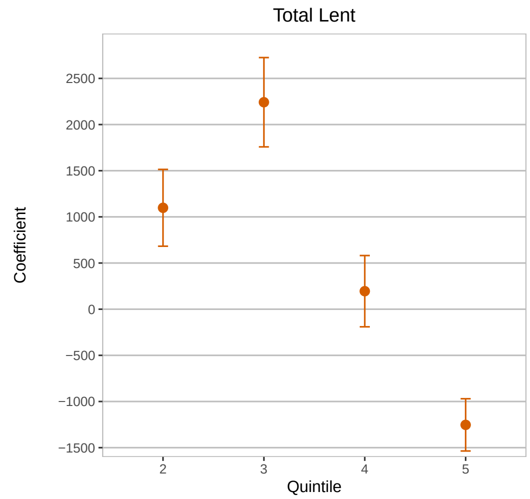
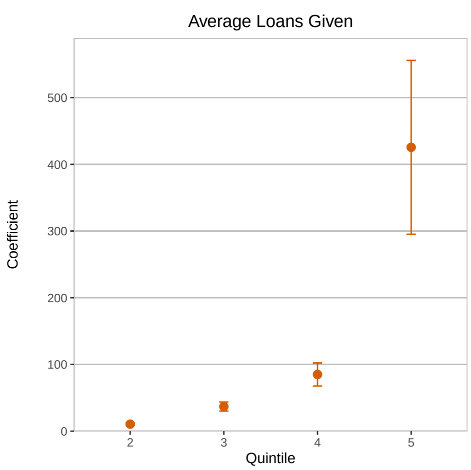


Figure 8: Lender Loans Given vs Amount Given with Lender Fixed Effects

(a)



(b)

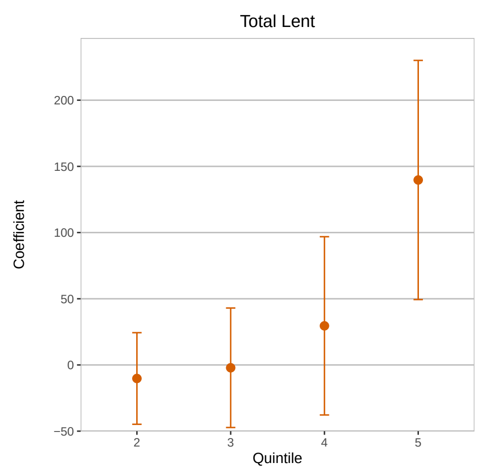


Figure 9: Experience Instrumental Variable

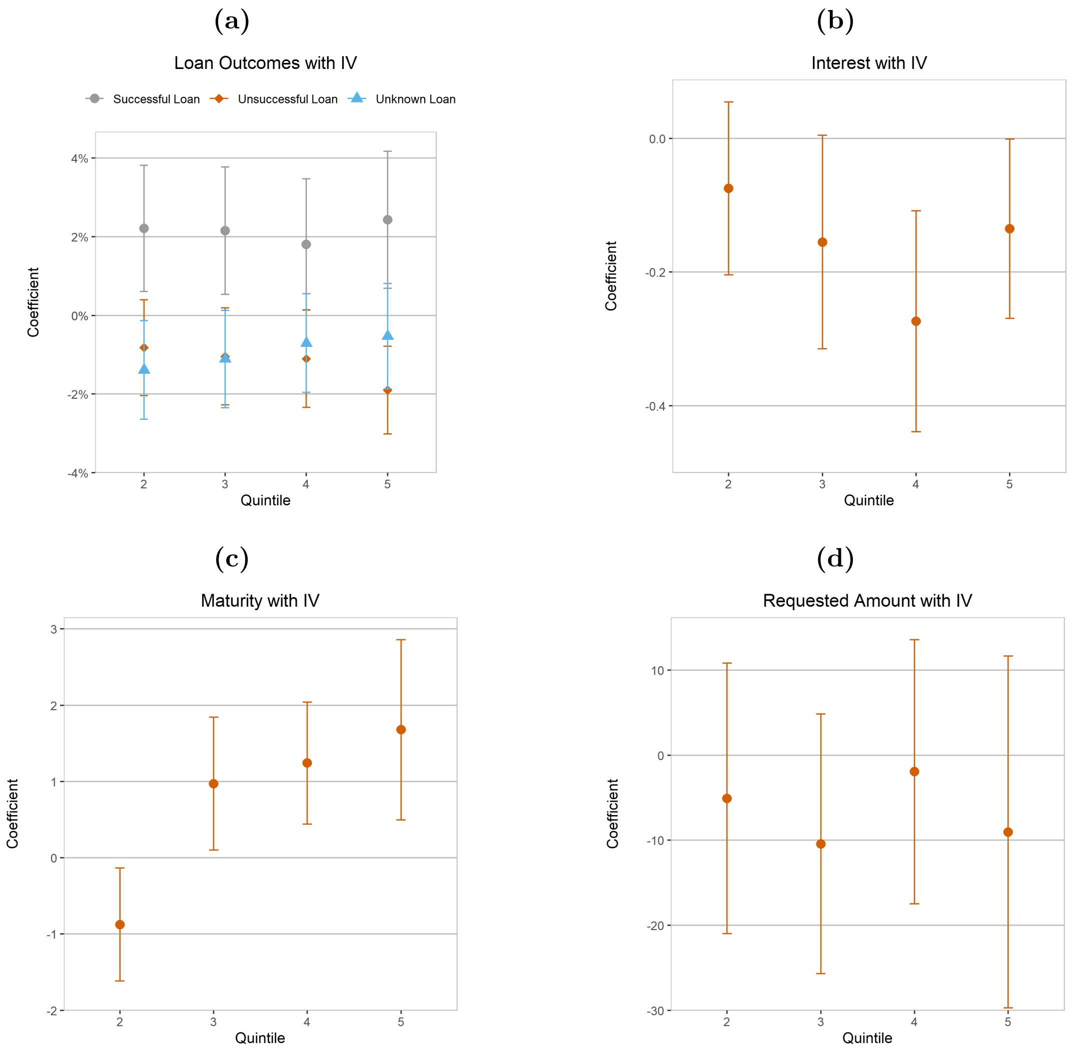


Figure 10: Distribution of Lender Profits

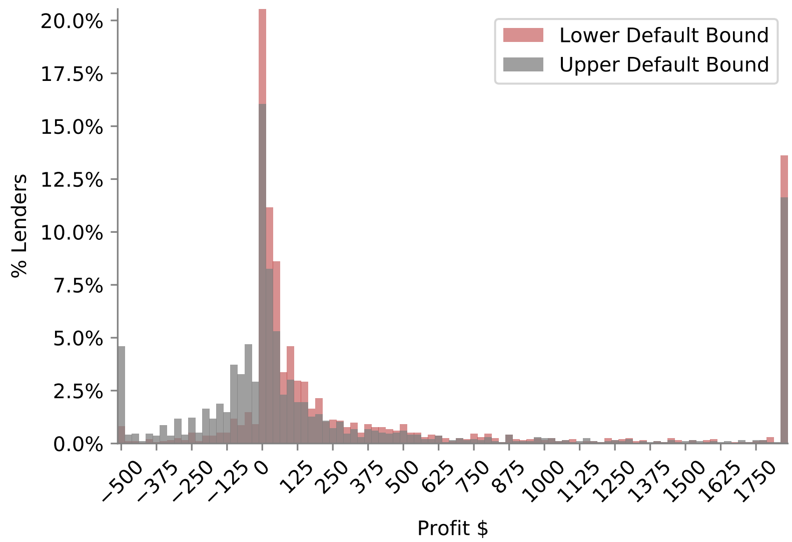


Figure 11: Distribution of Loans Given

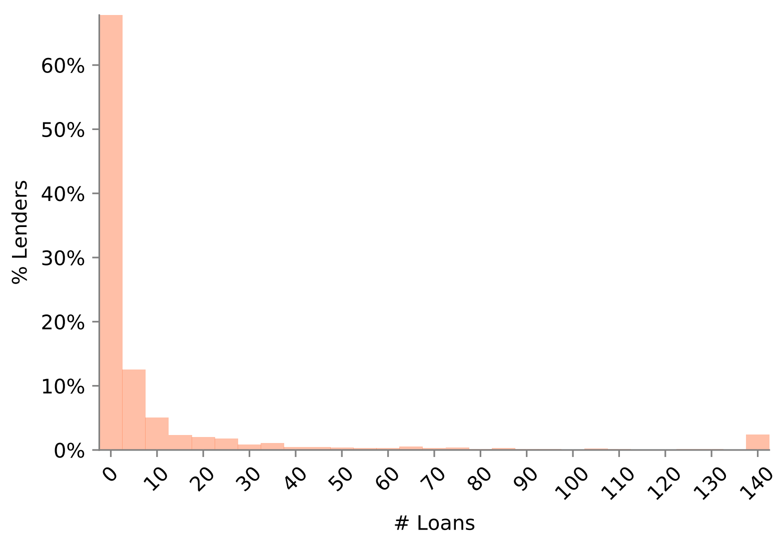


Figure 12: Overlapping Posts Loan Outcomes With Lender Fixed Effects

(a) **(b)**

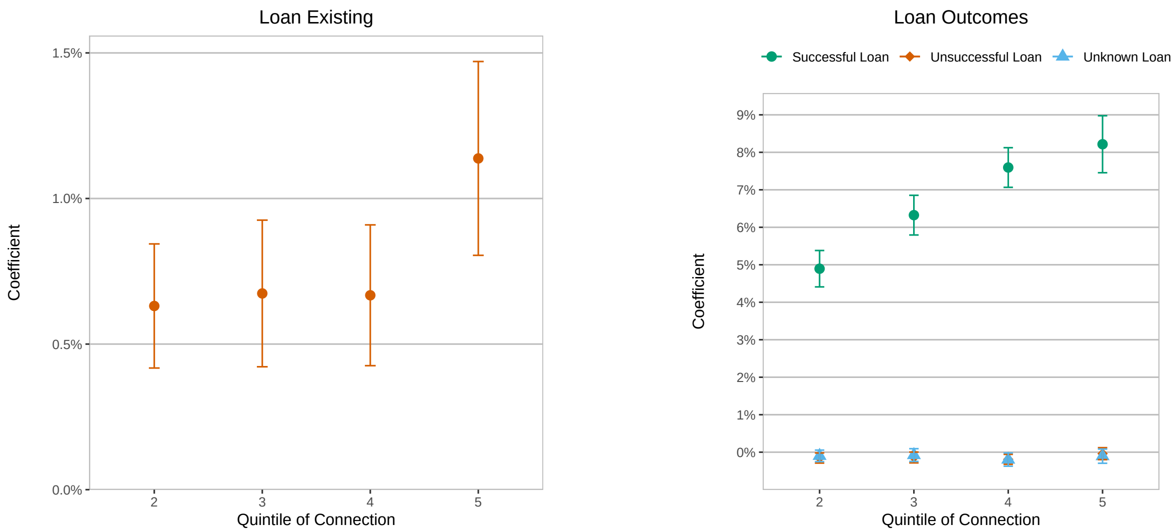


Figure 13: Overlapping Communities Loan Outcomes With Lender Fixed Effects

(a) **(b)**

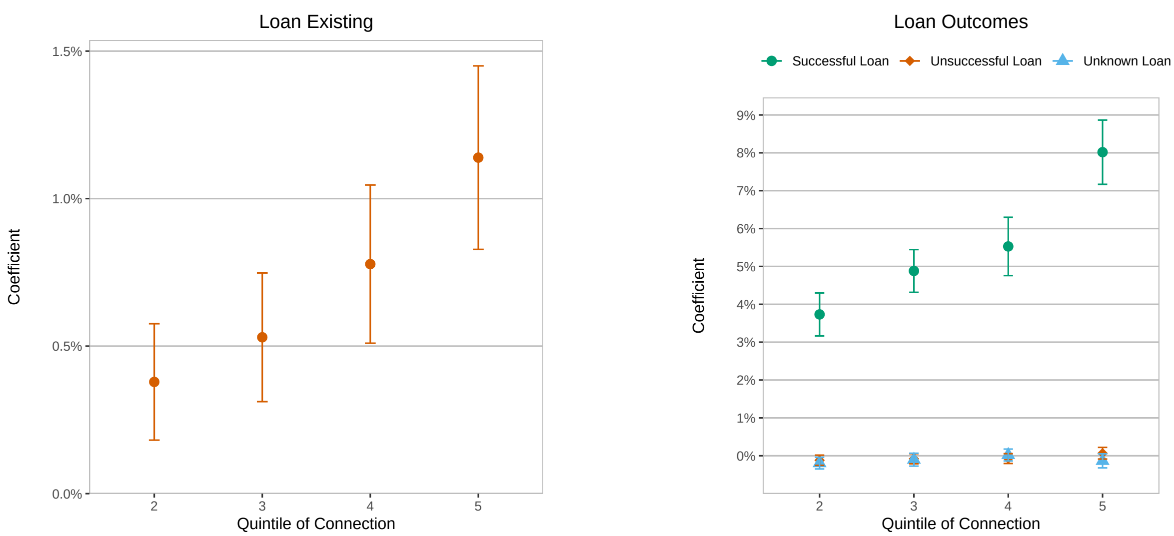
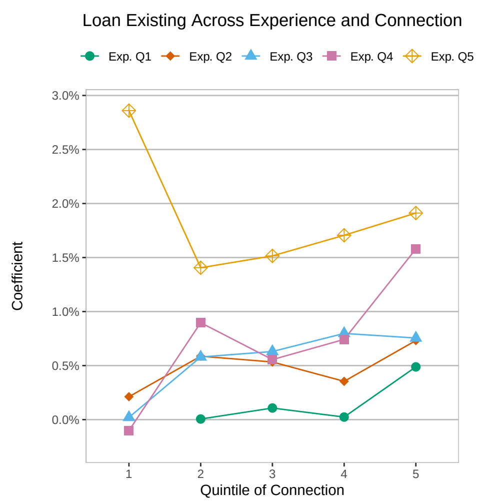
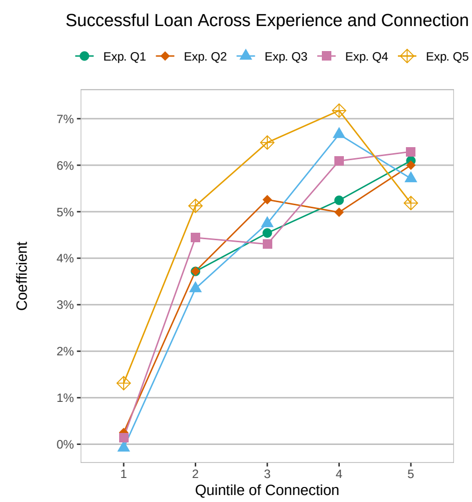


Figure 14: Connection Experience Interaction

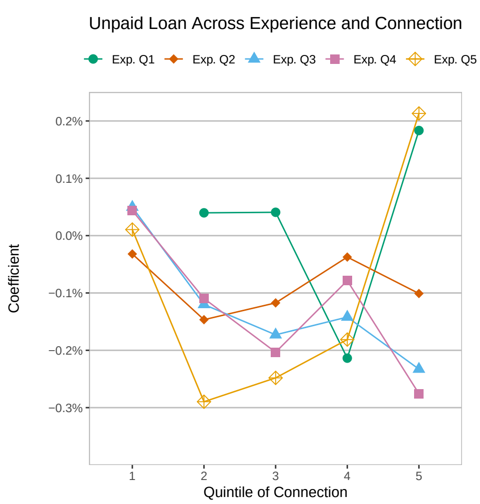
(a)



(b)



(c)



(d)

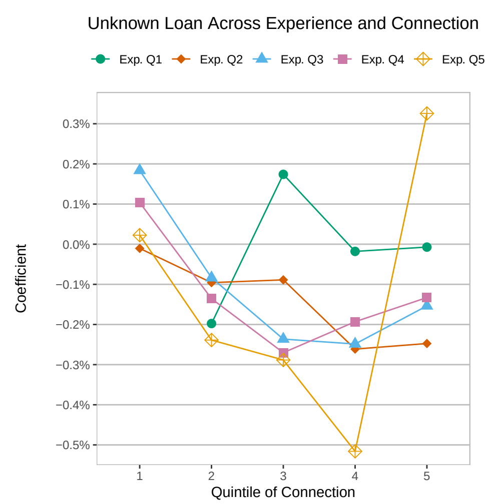


Table 1: Default Bounds Example

	Oct. 2021 Total = 953 Loans		
Paid	86%	?	0%
Unpaid	0%	?	4%
	Marked Paid	Unmarked	Marked Unpaid

Table 2: Summary Statistics

Loan requests with complete information (N=51,020)

	Mean	**SD**	**p10**	**p50**	**p90**
Requested Amount ($)	273	401	40	150	600
Promised Maturity (Days)	23	26	4	15	46
Promised Interest (% per month)	107	135	10	45	438
Converted Into Loan	68%				

Loans merged with requests (N=35,066)

	Mean	**SD**	**p10**	**p50**	**p90**
Loan Principal ($)	216	300	35	125	500
Effective Maturity (Days)	25	44	3	13	52
Promised Interest (% per month)	131	160	15	57	519
Default Lower Bound	4.2%				
Default Upper Bound	10.6%				

Table 3: Summary Statistics by Year

Year	Number of Loans	Average Loan Size	Median Monthly Interest Rate	Median Maturity
2016	426	$208	38.4%	14
2017	880	$211	45.4%	13
2018	3,340	$204	50.1%	13
2019	9,426	$201	61.3%	11
2020	10,248	$219	57.1%	12
2021	10,746	$231	58.8%	12

Table 4: Loan Determinants

	Loan Exists	
	First Request	Repeat Request
Maturity	-0.018	-0.015
	(0.000)***	(0.000)***
Requested Amount	-0.007	-0.002
	(0.000)***	(0.000)***
Promise Repay Amount	0.004	0.001
	(0.000)***	(0.003)**
In USA	0.197	0.434
	(0.000)***	(0.000)***
Payment Used	0.269	-0.022
	(0.000)***	(0.669)
Never Defaulted		1.549
		(0.000)***
Loans Outstanding		-0.091
		(0.000)***
Number of Requests		0.014
		(0.000)***
Loans Requested on a Day	-0.014	-0.012
	(0.000)***	(0.000)***
Weekend Dummy	-0.067	-0.084
	(0.101)	(0.007)**
Number of Words	-0.003	-0.003
	(0.000)***	(0.000)***
% Words Complex	-1.353	-0.899
	(0.000)***	(0.000)***
SMOG Index Syllables	0.147	0.036
	(0.000)***	(0.112)
Popular Words	-0.263	0.098
	(0.040)*	(0.181)
N	16,020	27,468

Table 5: Full Lender Statistics

Lender	Total Loans	Net Loaned Lowest Default	Net Loaned Highest Default	Received Lowest Default	Received Highest Default	Days Active
lender1	4,448	$4,190	$4,190	$899,135	$882,274	1,005
lender2	1,320	$14,107	$14,107	$270,229	$268,069	1,151
lender3	1,197	$23,291	$23,291	$350,858	$350,858	808
lender4	1,082	$6,195	$6,552	$277,449	$267,054	1,387
lender5	964	$27,419	$72,080	$460,276	$336,132	974
lender6	610	$680	$780	$64,838	$60,021	872
lender7	598	$8,499	$8,499	$184,030	$160,796	886
lender8	545	$6,145	$6,538	$82,481	$79,515	629
lender9	522	$1,537	$1,537	$165,401	$164,278	1,274
lender10	488	$10,156	$16,142	$218,439	$191,834	712

Table 6: Overlapping Posts Loan Outcomes

	Loan Exists	Successful Loan	Unpaid Loan	Unmarked Loan
Total Posts Overlap	0.060	0.209	0.006	−0.015
	(0.000)***	(0.000)***	(0.184)	(0.016)**
Maturity	−0.0002	−0.003	−0.0001	0.000
	(0.000)***	(0.000)***	(0.000)***	(0.29)*
Promised Repay Amount	0.000	−0.0002	0.000	0.000
	(0.561)	(0.000)***	(0.000)***	(0.000)***
Requested Amount	−0.00002	0.000	−0.0001	−0.0002
	(0.003)*	(0.000)***	(0.000)***	(0.000)***
N	490,376	490,376	490,376	490,376
R^2	0.013	0.055	0.007	0.009

Table 7: Overlapping Communities Loan Outcomes

	Loan Exists	Successful Loan	Unpaid Loan	Unmarked Loan
Total Communities Overlap	0.286	1.157	0.052	−0.018
	(0.000)***	(0.000)***	(0.008)***	(0.388)
Maturity	−0.0002	−0.003	−0.0001	0.000
	(0.000)***	(0.000)***	(0.000)***	(0.044)**
Promised Repay Amount	0.00000	−0.0002	0.0001	0.0001
	(0.498)	(0.000)***	(0.000)***	(0.000)***
Requested Amount	−0.00002	0.000	−0.0001	−0.0002
	(0.005)***	(0.00001)***	(0.000)***	(0.000)***
N	490,955	490,955	490,955	490,955
R^2	0.014	0.055	0.007	0.009

A Additional Tables

Table A1: Experience With Lender Fixed Effects

Dependent Variables:	Successful Loan	Unpaid Loan	Unmarked Loan	Maturity	Interest Rate	Promised Repayment	Requested Amount
Quintile Dummy 2	-0.001	-0.020***	0.022***	0.303	-0.006	18.987**	15.907***
	(0.009)	(0.007)	(0.007)	(0.404)	(0.045)	(7.370)	(6.084)
Quintile Dummy 3	-0.017	-0.019**	0.037***	0.794	-0.132**	38.152***	34.242***
	(0.010)	(0.009)	(0.008)	(0.507)	(0.055)	(9.635)	(7.983)
Quintile Dummy 4	-0.005	-0.037***	0.042***	1.519**	-0.195***	50.795***	46.021***
	(0.012)	(0.009)	(0.008)	(0.633)	(0.063)	(11.761)	(9.946)
Quintile Dummy 5	0.003	-0.040***	0.036***	1.657**	-0.331***	65.955***	57.767***
	(0.015)	(0.011)	(0.011)	(0.780)	(0.078)	(13.718)	(11.116)
Maturity	-0.001***	0.000	0.001***			5.494***	4.307***
	(0.000)	(0.000)	(0.000)			(0.600)	(0.479)
Promised Repayment	-0.001***	0.000***	0.000***	0.093***	0.003***		
	(0.000)	(0.000)	(0.000)	(0.013)	(0.001)		
Requested Amount	0.001***	-0.000***	-0.000***	-0.094***	-0.005***		
	(0.000)	(0.000)	(0.000)	(0.015)	(0.001)		
Interest Rate				-4.313***			
				(0.154)			
Lender Fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	19,096	19,096	19,096	19,096	19,096	19,096	19,096
R^2	0.309	0.192	0.397	0.383	0.253	0.317	0.312

Clustered (lender) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table A2: Experience With Week Fixed Effects

Dependent Variables:	Successful Loan	Unpaid Loan	Unmarked Loan	Maturity	Interest Rate	Promised Repayment	Requested Amount
Quintile Dummy 2	0.107***	-0.022**	-0.085***	-1.513*	-0.164***	50.894***	45.196***
	(0.012)	(0.009)	(0.010)	(0.790)	(0.057)	(8.314)	(6.628)
Quintile Dummy 3	0.174***	-0.049***	-0.125***	-1.164*	-0.384***	69.051***	65.300***
	(0.015)	(0.011)	(0.010)	(0.672)	(0.061)	(13.093)	(9.438)
Quintile Dummy 4	0.211***	-0.076***	-0.135***	-2.483***	-0.461***	84.813***	81.951***
	(0.013)	(0.009)	(0.010)	(0.819)	(0.055)	(14.342)	(11.162)
Quintile Dummy 5	0.214***	-0.070***	-0.145***	-1.804*	-0.380***	46.219***	38.922***
	(0.011)	(0.008)	(0.009)	(0.949)	(0.073)	(13.218)	(9.240)
Maturity	-0.002*	0.001	0.001			6.691**	4.588**
	(0.001)	(0.001)	(0.001)			(3.072)	(2.012)
Promised Repayment	0.000***	-0.000	-0.000***	0.057**	0.001***		
	(0.000)	(0.000)	(0.000)	(0.023)	(0.001)		
Requested Amount	-0.001***	0.000	0.000***	-0.045	-0.004***		
	(0.000)	(0.000)	(0.000)	(0.029)	(0.001)		
Interest Rate				-5.449***			
				(1.174)			
Week Fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics							
Observations	985	985	985	985	985	985	985
R^2	0.505	0.301	0.489	0.439	0.408	0.400	0.395

Clustered (week) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table A3: Overlapping Posts Connection With Lender Fixed Effects

Dependent Variables:	Exist	Successful Loan	Unpaid Loan	Unmarked Loan
Model:	(1)	(2)	(3)	(4)
Variables				
Quintile Dummy 2	0.006***	0.049***	-0.002**	-0.001
	(0.001)	(0.002)	(0.001)	(0.001)
Quintile Dummy 3	0.007***	0.063***	-0.001*	-0.001
	(0.001)	(0.003)	(0.001)	(0.001)
Quintile Dummy 4	0.007***	0.076***	-0.002***	-0.002**
	(0.001)	(0.003)	(0.001)	(0.001)
Quintile Dummy 5	0.011***	0.082***	0.000	-0.001
	(0.002)	(0.004)	(0.001)	(0.001)
Maturity	0.000***	-0.003***	0.000***	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)
Promised Repayment	0.000	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Requested Amount	0.000**	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Fixed-effects				
lender	Yes	Yes	Yes	Yes
Fit statistics				
Observations	490,416	490,416	490,416	490,416
R^2	0.011	0.057	0.007	0.009

Clustered (lender) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table A4: Overlapping Posts Connection With Lender Fixed Effects

Dependent Variables:	Exist	Successful Loan	Unpaid Loan	Unmarked Loan
Model:	(1)	(2)	(3)	(4)
Variables				
Quintile Dummy 2	0.004***	0.037***	-0.001*	-0.002**
	(0.001)	(0.003)	(0.001)	(0.001)
Quintile Dummy 3	0.005***	0.049***	-0.001	-0.001
	(0.001)	(0.003)	(0.001)	(0.001)
Quintile Dummy 4	0.008***	0.055***	-0.001	0.000
	(0.001)	(0.004)	(0.001)	(0.001)
Quintile Dummy 5	0.011***	0.080***	0.001	-0.001
	(0.002)	(0.004)	(0.001)	(0.001)
Maturity	0.000***	-0.003***	0.000***	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)
Promised Repayment	0.000	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Requested Amount	0.000**	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Fixed-effects				
lender	Yes	Yes	Yes	Yes
Fit statistics				
Observations	490,392	490,392	490,392	490,392
R^2	0.011	0.057	0.007	0.009

Clustered (lender) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*