Financial Innovation and Borrowers: Evidence from Peer-to-Peer Lending*

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JOB MARKET PAPER

Abstract
I study how the emergence of the financial technology-driven public market for consumer debt in the form of peer-to-peer (P2P) lending affects credit provided by traditional financial intermediaries. I show that innovation in the way hard information is processed influences both the supply of and the demand for credit from other financial intermediaries. On the supply side, credit intermediaries rely on certification by P2P lenders in their decision to increase access to credit for borrowers. This finding is consistent with increased accuracy of screening and information cascading to other lenders when multiple lenders make credit decisions sequentially. On the demand side, P2P lending induces refinancing of expensive credit card debt by highly creditworthy borrowers and increases debt-financed consumption by financially-constrained borrowers. I find no evidence that increased access to credit results in higher delinquencies. The results suggest that P2P lending mitigates financing frictions through repricing of credit and reduced credit rationing due to lower costs and/or improved accuracy of costly state verification. I conclude that financial technology innovation can resolve some imperfections in the credit market.

Keywords: access to credit, credit rationing, disintermediation, financial innovation, fintech, household finance, peer-to-peer lending

JEL Classification Numbers: G21, G23, D14

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"Savers have never had a worse deal but for most borrowers, credit is scarce and costly. That seeming paradox attracts new businesses free of the bad balance sheets, high costs and dreadful reputations which burden most conventional banks."

(The Economist, 2014)

1 Introduction

The consumer credit market is one of the largest, most important credit markets, with outstanding credit of $3.5 trillion in 2015 (FED, 2016). A number of fintech-driven innovators have focused on entering this market, seeing frictions they can overcome and potential for profitable entry. Sources of imperfections highlighted in the literature include information asymmetries and adverse selection (Stiglitz and Weiss, 1981), high costs of debt refinancing (Brito and Hartley, 1995), and imperfect competition (Parlour and Rajan, 2001). Credit market features consistent with frictions include credit card companies pooling borrowers of diverse credit quality with similar rates, high rates on credit cards for high quality borrowers, and credit rationing (e.g., Stango and Zinman, 2009).

This paper studies how peer-to-peer (P2P) lending impacts borrowers. I investigate this impact empirically by looking at credit provided by P2P lending platforms and traditional financial intermediaries, such as banks. I examine how getting a P2P loan affects access to credit from banks, consumers' borrowing patterns, excess borrowing and delinquencies. I focus on P2P lending as it is by far the most successful fintech innovation in the consumer credit market.[1] Despite media attention and a recent regulatory debate questioning the benefits of P2P lending, little is known about the impact of this technological innovation on borrowers in general, and on credit supply in particular.

The main innovation of P2P lending is the launch of lending platforms that allow direct matching of borrowers and lenders. P2P lending platforms allow individual borrowers to request a loan online, and lenders to screen loan applications and decide how much to lend. These fintech companies have created a public market for consumer debt, akin to the bond market, that did not exist before 2006. A second technological innovation is the use of fully-automated algorithms to price and underwrite

[1] The New York Times, for example, has characterized peer-to-peer lending as a "rare thing, scarcely seen in the financial world since the debut of the A.T.M. or microfinancing: an innovation to help regular people" (NYT, 2014).

loans to lower screening costs.[2] Thus, P2P lending is an innovation in the lending technology rather than in the product space. P2P loans are unsecured amortizing loans. The average loan size is $12,767 and typical maturities are 3 and 5 years. The two largest P2P lending platforms in the U.S. originated $16.1 billion in loans from Q1 2006 to Q3 2015.[3] Although still relatively small in size, P2P lending has grown rapidly and is expected to grow to $150 billion per year by 2025 (PwC, 2015).

In a world with complete markets and no frictions, there would be no need for financial innovation and if it occurred, it would be irrelevant as it would not change the fundamentals: demand and supply of credit balance, borrowers obtain enough credit to smooth consumption, and borrower risk is accurately reflected in interest rates. In such a setting, P2P lending would not affect the overall credit supply to borrowers, but the increased lending from P2P institutions would be perfectly offset by reductions in lending by other financial institutions. I call this the substitution hypothesis.

Predictions change and expand if one allows for imperfections. One of the most studied imperfections is asymmetric information leading to market distortions, such as pooling of borrowers (Akerlof, 1970; Leland and Pyle, 1977) and adverse selection (Stiglitz and Weiss, 1981). In the pooling equilibrium, financial intermediaries set interest rates based on average pricing. This creates credit mispricing as borrowers of high credit quality subsidize borrowers of low credit quality. Adverse selection can also create social costs of a market breakdown in the form of credit rationing, under which riskier borrowers are denied credit (Stiglitz and Weiss, 1981). If P2P lending improves the quality of information, some previously credit-rationed borrowers should be given access to credit, and the reduction in pooling should lead to benefits in pricing of debt for the best quality borrowers.

But do P2P lenders reduce information asymmetries? Given the P2P process that I describe below, it appears that they do not generate any new soft information not available to existing lenders. Rather, if they do improve information, it is likely to come through leveraging information from institutional lenders who are well positioned to have insights into credit market conditions and

[2] Banks incur some additional costs, such as costs to operate the branch network and compensate credit officers.

[3] This compares to $924.2 billion in revolving credit and $2.57 trillion in non-revolving credit outstanding in the U.S. in Q3 2015 (FED, 2016).

are active in deciding on whether or not to fund loans. Allen and Gale (1998) argue that public markets can be superior to financial intermediaries in providing funding because diversity of opinion is valuable when information is inexpensive. In P2P lending, fintech companies attract investors with different proprietary screening algorithms. The combined opinions of these investors may result in more accurate screening because of the "wisdom of the crowd".[4] Granular pricing of P2P loans also supports improved information processing.

The literature on signalling when screening is costly and imprecise suggests that improvements in information processing may give rise to certification. The idea that actions by one party may trigger the same actions by other parties was explored in the context of informational cascades (e.g., Welch, 1992; Banerjee, 1992; Bikhchandani, Hirshleifer and Welch, 1992).[5] In these models, agents gain useful information from observing actions of others and may optimally and rationally follow these agents when decisions are made sequentially. This implies that other credit intermediaries may rely on a signal from P2P lenders in their decision to increase access to credit after observing a P2P loan.

A third possibility associated with P2P lending is that it does not improve fundamentals, but rather offers a new way for financial intermediaries to take advantage of behavioral biases in borrowers' decision making. Laibson (1997), for example, shows that financial innovation in the form of instantaneous credit eliminates commitment and leads to overborrowing. Bizer and DeMarzo (1992) develop a model where sequential banking increases the indebtedness of borrowers and makes default more likely, which has negative externalities for existing lenders. This leads to a prediction that P2P lending results in overborrowing, which should be reflected in higher delinquency rates.

The tests I introduce in the paper seek to differentiate between these alternative views of P2P lending: no change in fundamentals, reducing information asymmetries, and exploiting behavioral biases of consumers. A key variable in the tests to follow is the quantity of credit for credit-constrained

[4]There is also anecdotal evidence that investors in P2P lending may be able to screen borrowers better than traditional credit intermediaries as they are not subject to regulatory restrictions that limit discriminatory lending based on location (WSJ, 2016). Balyuk and Davydenko (2016) provide empirical evidence on the underwriting ability of P2P lending platforms and the screening ability of investors in P2P lending.

[5]These models are build based on Townsend's (1979) costly state verification framework. Townsend (1979) notes that "the decision to verify might act as a signal of the realizations".

borrowers, which is predicted to increase under the information asymmetry hypothesis and not otherwise. A second variable I track is the extent of pooling of borrowers and if this changes around the introduction of the P2P platform. The key variable I focus on to address the behavioral hypothesis is the delinquency rate, the improved information hypothesis suggesting no change in delinquencies while the behavioral hypothesis suggesting increases around exposure of borrowers to P2P lending.

I test the impact of P2P lending using data from Prosper Marketplace, one of the largest P2P lenders in the U.S. The data set contains detailed credit bureau and self-reported information on approved and rejected loan applications. The median applicant on the platform has a strong borrower profile – high credit score, high income and long credit history – but lacks collateral and capacity to take on more debt. While most of these borrowers are creditworthy, some are likely credit constrained.

The most convincing tests in the paper take concerns about identification seriously. This is an important issue because of the possibility that those who receive loans from P2P lending platforms may be systematically different from other borrowers and it might be those unobserved characteristics that drive outcomes rather than P2P lending. Three features of Prosper's platform facilitate identification of the causal effect of P2P loans on borrowers. First, Prosper tracks repeat borrowers (those who submit applications several times), which allows me to construct a panel of borrowers and observe changes in their financials after obtaining a P2P loan. Second, the loan amount and the interest rate are set prior to funding. Thus, it is the fraction of the requested loan amount funded by investors that determines whether borrowers get P2P loans or not. Third, a P2P loan can be extended only if investor commitments cross 70% of the requested amount. I use this funding threshold in regression discontinuity design (RDD) to identify the causal effect of obtaining the loan.

I first examine whether P2P lending affects access to credit. Contrary to the substitution hypothesis, and consistent with P2P affecting information asymmetries and credit rationing, I find that not only do marginal borrowers who get access to P2P lending expand their credit through this channel, but traditional credit intermediaries expand their credit supply to these customers. I start by examining credit limits on revolving accounts, such as credit cards and lines of credit.[6] I exploit within-borrower variation in credit limits and compare outcomes for borrowers who do and do not receive P2P loans in fixed effects regressions. I show that P2P lending is associated with an increase in credit limits of \$990 or 2.5% relative to the mean on the first application. The increase is largest (6.1%) for borrowers of the lowest credit quality. In similar tests, I observe an increase in the number of revolving accounts, although smaller in magnitude (1.3%). I then use the fact that the probability of loan origination jumps discretely by 40% above the funding threshold in the RDD analysis. The RDD results support the above findings. I find that P2P lending leads to an increase in credit limits for marginally-funded borrowers of 105.3%. I observe that these borrowers get more mortgages so the increase may be larger because of home equity lines of credit they obtain. These results suggest that other credit intermediaries take P2P lending into account when making decisions to increase access to credit. The increase is coming primarily from existing lenders. Since the total debt of borrowers is higher after a P2P loan, the expanded access to credit is unlikely due to improved financials.

On the demand side, I find evidence of both credit repricing for high quality borrowers and increased use of debt by marginal borrowers. There clearly is some substitution for many borrowers. The results of fixed effects regressions show that P2P lending is associated with a decrease in revolving balances of 7.7% and revolver utilization of 10.3% relative to the mean. But, critically, the information asymmetry hypothesis is that the extent of substitution is related to the pre-existing costs of pooling, with the best quality borrowers benefiting most from the change. This is precisely what I find. The decrease in balances is stronger for borrowers of higher credit quality. These findings suggest that creditworthy borrowers refinance their expensive credit card debt out of P2P loans and are consistent with credit repricing. The RDD analysis, however, shows that P2P lending leads to an increase in revolving balances (137.9%) and revolver utilization (51.2%) for marginally-funded borrowers. These borrowers seem to be of lower credit quality and are likely more credit-constrained than other borrowers in the sample. This finding is consistent with these borrowers increasing debt-financed consumption because of reduced credit rationing. Given that marginal borrowers increase

[6] P2P loans are treated as installment debt so they are not part of revolving accounts.

the use of revolving debt but their access to credit from traditional credit intermediaries goes up nonetheless, I conclude that the increase in the credit supply is not driven by borrowers becoming more resilient to short-term liquidity shocks after getting a P2P loan.

Finally, to help address the behavioral hypothesis that P2P leads to overborrowing, I track the total debt of borrowers and delinquencies. I find that the total debt increases by around 4.5% for all borrowers and 82.3% for marginally-funded borrowers. However, I find that increased access to credit and higher debt do not lead to higher delinquency rates. This result is inconsistent with overborrowing because of behavioral biases, as in Laibson (1997). One concern with my methodology is that identification comes from repeat borrowers and I do not observe the outcomes for borrowers who applied for a P2P loan only once. This sample attrition may bias the empirical results if it were borrowers of higher credit quality who return for another loan. I show that the opposite is true.

Collectively, the hypothesis that best connects my findings is that financial technology innovation in the form of P2P lending gives rise to certification as information cascades through multiple lending relationships and may be able to reduce financing frictions in the consumer credit market.

The paper contributes to the literature on financial innovation (e.g., Boot and Thakor, 1997; Hauswald and Marquez, 2003; Keys, Mukherjee, Seru, and Vig, 2010). Whereas most of the literature focuses on financial innovation in the product space, I examine the technology side of financial innovation. This paper shows that financial innovation impacts borrowers by increasing their access to credit and reducing financing frictions. To the best of my knowledge, this is the first paper showing that P2P lending can alleviate personal financing constraints of borrowers. The paper also contributes to the literature on the supply of credit under adverse selection (e.g., Dell'Ariccia, Friedman, and Marquez, 1999; Marquez, 2002), credit rationing (e.g., Stiglitz and Weiss, 1981; Bester, 1985; Arnold and Riley, 2009), and information cascades (e.g., Welch, 1992; Banerjee, 1992; Bikhchandani, Hirshleifer and Welch, 1992). I show that P2P lending can ease frictions in consumer lending through correcting mispriced credit and mitigating credit rationing.

The paper also speaks to the household finance literature (e.g., Jappelli, 1990; Laibson, 1997;

Gross and Souleles, 2002; Campbell, 2006) and to the credit card literature (e.g., Brito and Hartley, 1995). I provide large-scale empirical evidence on how financial technology innovation impacts consumer credit choices in terms of debt refinancing and debt-financed consumption. High balances on credit cards with high interest rates is puzzling. Researchers have proposed both rational and behavioral explanations of this puzzle. The evidence in this paper is consistent with the rational explanation, i.e. high credit card balances are caused by search or switching frictions resulting from transaction costs and/or asymmetric information. I show that once information asymmetry is reduced, consumers refinance their expensive credit card debt.

Finally, the paper relates to the growing literature on P2P lending (e.g., Bachmann et al, 2011; Duarte, Siegel and Young, 2012; Ravina, 2012; Lin, Prabhala, and Viswanathan, 2013). To date, the literature focused on determinants of funding on P2P lending platforms. In contrast, this paper uses P2P lending as a setting to explore the effect of financial innovation on supply and demand for credit from traditional credit intermediaries. The paper has important policy implications. The current regulatory debate questions the benefits of P2P lending and calls for stricter regulation of these platforms. My results suggest that P2P lending may facilitate access to cheaper credit and generate a feedback effect on the supply of credit by credit intermediaries without leading to overborrowing.

The remainder of the paper is organized as follows. Section 2 describes P2P lending. Section 3 gives an overview of the data. Section 4 describes the empirical methodology. Section 5 presents the empirical results on the supply of credit while Section 6 presents the results on the credit demand and delinquencies. Section 7 discusses the external validity of the analysis and Section 8 concludes.

2 Peer-to-Peer Lending

2.1 The Innovation of Peer-to-Peer Lending

The traditional credit market features significant market power of credit intermediaries vis-a-vis borrowers and information opaqueness of the lending process. This situation is the result of certain credit market imperfections, such as transaction costs and information asymmetry. Pooling of consumers of different credit quality under asymmetric information made it optimal for banks to offer average pricing on credit products, specifically credit cards, and refuse credit to certain categories of borrowers. This led to market failures where borrowers of high credit quality cross-subsidized borrowers of low credit quality and some marginally creditworthy borrowers who could not differentiate themselves from borrowers of low credit quality were credit-rationed.

The seminal paper by Stiglitz and Weiss (1981) describes the distortions in lending that arise because of asymmetric information. Imperfect (hidden) information about the creditworthiness of borrowers makes it difficult for lenders to distinguish between borrowers of good types and bad types. In order to attract financing, borrowers of bad types are willing to pay high interest and give a higher stake of their future income to lenders. But these are also the borrowers who default more. This creates adverse selection as more risky borrowers sort into offers with higher interest rates so an increase in interest rates leads to lower profits. Thus, it is optimal for lenders to set interest rates based on average pricing conditional on the distribution of borrowers who apply for loans in terms of their creditworthiness. The equilibrium outcome in the lending market is the pooling equilibrium (as in Akerlof, 1970). Another outcome of asymmetric information is moral hazard (hidden action). The share of pledgeable future income that is left for debt repayment directly depends on the actions of borrowers. The ex-post returns of lenders suffer if borrowers of low credit quality become delinquent. Adverse selection together with moral hazard result in the market breakdown in the form of credit rationing, under which some borrowers that are riskier than a certain cut-off do not get credit ex ante since providing credit to these borrowers will lower lenders' returns ex post (Stiglitz and Weiss, 1981; Stiglitz, 1990).[7] The role of P2P lending in the credit market merits closer investigation as this disintermediation of lending seems counterintuitive to the emergence of financial intermediaries as a result of credit market imperfections (e.g., Diamond, 1984; Boyd and Prescott, 1986). I argue that P2P lending can resolve some of the credit market imperfections that traditional credit intermediaries could not resolve.

[7]See Berger and Udell (1992) for the discussion of the empirical significance of credit rationing.

Peer-to-peer (P2P) lending emerged as a financial disruptor in the consumer credit market.[8] It directly matches borrowers to lenders, bypassing traditional credit intermediaries. It is considered one of the most prominent innovations in consumer finance over the past decade, comparable in its impact to introduction of ATM or microfinancing[9]. The innovative approach to lending introduced by P2P lending platforms makes consumer credit more cost-effective by reducing transaction costs, in particular through eliminating fixed investments into the branch network, and improving the quality of customer experience. The costs of P2P lending platforms are allegedly only one third of those of commercial banks[10].

P2P lending also reduces the extent of information asymmetry in the consumer lending market. Availability of a loan application for funding to multiple prospective lenders makes borrowers less dependent on differences in underwriting standards and distance from lenders. Although P2P lending lets less sophisticated investors enter the lending game, the P2P lending market is now dominated by institutional investors[11]. Institutional lenders on P2P platforms have different proprietary algorithms to screen for creditworthy borrowers and this heterogeneity increases the chances of getting a loan, especially for borrowers of marginal credit quality. P2P lending made the application screening process more efficient by decreasing the cost of state verification[12]. P2P lending platforms also allow multiple lenders to co-invest in one loan thus providing more diversification benefits to lenders via fractional ownership of loan amounts.

There are two major lending platforms that account for 98% of the P2P market in the U.S., namely Prosper Marketplace (Prosper) and Lending Club[13]. I estimate that the cumulative amount

[8] Jefery and Arnold (2014) discuss peer-to-peer lending as a disrupting innovation threatening traditional banking. They highlight inefficiencies and frictions that P2P lending overcomes or mitigates.

[9] "Loans that Avoid Banks? Maybe Not", The New York Times, May 3, 2014.

[10] See "Peer-to-Peer Lending: Banking without Banks", The Economist, March 1, 2014.

[11] "Loans that Avoid Banks? Maybe Not", The New York Times, May 3, 2014.

[12] Several papers report evidence consistent with the additional soft information that used to be extracted by investors in P2P lending platforms and certification mechanisms that arise endogenously in P2P lending. These papers include Duarte, Siegel, and Young (2012), Larrimore, Jiang, Larrimore, Markowitz, and Gorski (2011), Michels (2012), Lin, Prabhala, and Viswanathan (2009), Hildebrand, Puri, and Rocholl (2010), Weiss, Pelger, and Horsch, (2010), and Berger and Gleisner (2009) among others. This additional soft information is no longer available on Prosper and P2P lenders predominantly rely on hard information in screening loan applications.

[13] See "Peer-to-Peer Lending: Banking without Banks", The Economist, March 1, 2014.

of loans originated on these platforms was \$16.1 billion of loans provided to 1.16 million borrowers from Q1 2006 to Q3 2015. The cumulative amount of listings on P2P lending platforms over the same period was \$93.9 billion in loans requested by 7.1 million borrowers. The P2P lending market was at least \$2.75 billion in Q3 2015 in terms of loans originated and the demand was at least \$13.6 billion in terms of loan listings on these two platforms. PricewaterhouseCoopers expects the market to grow to at least \$150 billion per year by 2025 (PwC, 2015).

P2P loans are unsecured. The ratio of loans taken with the purpose of credit card repayment or other debt consolidation has grown from under 60% in 2007 to more than 80% in 2015 both in terms of the number of originated loans and their dollar amount. There is, however, no enforcement of the intended use of credit. Lenders on P2P platforms cannot force borrowers to use the loan proceeds for the stated purpose and there is no other mechanism to ensure accountability. Thus, it is unclear whether P2P borrowers indeed use the proceeds for debt repayment and how this changes their relationships with banks.

2.2 Implications for Borrowers

Financial innovation in the form of disintermediated lending can change the equilibrium in consumer credit markets in one of two ways. The first possibility is that a technological shock reduces the cost of credit screening and leads to repricing of consumer credit.[14] This induces borrowers to refinance their existing debt by obtaining credit from cheaper sources. Thus, the first prediction is that creditworthy borrowers switch from banks to P2P lending platforms. I expect the switching to be present even if P2P lenders cannot perfectly discriminate between borrowers of different credit quality. Moving from a state with average credit cards pricing to a state with marginal pricing that is based on more detailed segmentation of borrowers into risk categories is expected to result in substitution of P2P loans for bank debt. I expect this effect to be especially strong with respect to

[14] Using data on interest rates requested by borrowers in the auction model that existed in P2P lending in early years, Butler, Cornaggia, and Gurun (2013) study the effect of access to finance on consumers' borrowing decisions using a difference-in-differences approach around an exogenous change in an interest rate ceiling. They find that better access to local finance decreases interest rates that borrowers request. This suggests that the interest rate is an important determinant of borrowers' willingness to substitute P2P loans for credit from incumbent financial intermediaries.

revolving accounts (e.g., credit cards). These are the accounts with the highest interest rates, which become even higher if borrowers roll-over their revolving balances. Consumers also value short-term liquidity to insure against any adverse shocks to consumption and are willing to sacrifice returns to satisfy their liquidity demand (e.g., see Bryant, 1980 and Diamond and Dybvig, 1983). Thus it seems that paying down credit card debt is the first-best choice for borrowers of high credit quality. There may also exist a category of highly creditworthy borrowers who were unwilling to take credit under high prevailing interest rates but became willing to take loans when P2P lending emerged. Thus, I predict an increase in the total debt of borrowers as a result of this financial innovation.

The second possible effect is due to the ability of financial innovation to mitigate credit-rationing. Financial innovation that improves the information environment and the loan underwriting process is expected to result in credit provided to those categories of borrowers who are willing and able to repay debt but were credit-rationed because of information asymmetry. This effect likely prevails in the subsample of borrowers with marginal credit quality. Financial innovation may also give rise to certification. Ex ante banks credit ration some borrowers, then they learn about the credit quality of their clients and optimally adjust credit limits ex post based on their updated beliefs about borrower types. If P2P lending is more efficient in screening borrowers, it may serve as a certification device for traditional credit intermediaries. Banks may infer changes in the credit quality of their clients by observing that a borrower was granted a P2P loan. Although new loans are reflected in FICO scores with a substantial lag (see Keys, Mukherjee, Seru, and Vig, 2010 for a discussion), P2P loans are reflected in credit reports within approximately a month's time which makes information about obtaining a P2P loan promptly available to traditional financial intermediaries. If banks respond to P2P lending by improving access to credit for P2P borrowers either in the form of higher credit limits or additional credit offers, I expect to see an increase in revolving credit limits.

On the demand side, I expect financially constrained borrowers to increase their utilization of debt and credit balances as they move away from suboptimal credit levels induced by credit rationing towards the optimal levels of debt. It is unclear, however, whether any increase in credit utilization fostered by financial innovation is optimal for consumers or leads to overborrowing. The former should have positive implications for consumption, utility, and welfare. The latter increases the likelihood of personal financial distress in the form of delinquencies or personal bankruptcies. Since drawing any conclusions on the optimality of consumer credit choices requires additional information such as interest rates on existing credit products and their change over time as well as personal wealth variables, I cannot directly speak to the implications of P2P lending for consumer welfare.

Despite existing academic evidence on the determinants of funding success and lender behavior in P2P lending markets[15], the existing literature does not address the impact of P2P lending on credit choices of borrowers or credit supply. Neither has the literature looked at P2P lending from the perspective of its ability to mitigate credit-rationing in consumer credit markets. This paper bridges this gap in the literature and studies how financial innovation in the form of P2P lending impacts borrower credit choices and access to credit by these borrowers from traditional financial intermediaries.

2.3 Prosper's P2P Lending Platform

In order to assess the impact of financial innovation on borrowers, I look at outcomes of obtaining a loan on Prosper's lending platform. Prosper was launched in November 2005 and opened its platform to the general public in February 2006. Prosper's business model was initially an auction-type model where prospective borrowers would choose the loan amount and the reservation rate, i.e. the maximum interest rate they were willing to pay, and lenders (also called investors) would bid on the loan application (called listing). In December 2010, Prosper switched to a model with pre-set interest rates, which is similar to Lending Club's model, where investors would post their commitments to finance the entire loan or a fraction. Prosper also made some additional changes to

[15] Bachmann et al (2011) provides a comprehensive literature review of the academic papers published from the launch of peer-to-peer lending in 2005 to 2010. The earlier papers mostly focus on the determinants of P2P lending, specifically the probability of the loan being funded, the interest rate, and the ex-post default rate. Morse (2015) gives a good survey of the recent literature on P2P crowdfunding. The paper discusses information frictions that can be mitigated by P2P lending. The discussion focuses on risk and portfolio choice of lenders as well as pricing and access to finance benefits for the borrowers.

its lending process, e.g., increasing the minimum loan amount from $1,000 to $2,000 and introduced the partial funding option. After completing its registration with the U.S. Securities and Exchange Commission in July 2009, Prosper has been obliged to make information on all loan applications public as each listing is regarded a separate security. Prosper provides more detailed information to existing and prospective investors via its public API service.

The lending process on Prosper starts with a loan application. A prospective borrower requires a bank account, which means that P2P loans are not provided to the unbanked population. The borrower submits the requested loan amount, her annual income, and employment status. Prosper makes a soft credit check into the borrower's credit history and pulls her credit report from the Experian credit bureau. The credit report, inter alia, contains information on the borrower's credit score, debt, number of accounts in the borrower's name, credit utilization ratios and balances on revolving, installment, and mortgage accounts. Prosper then generates an interest rate quote (called borrower rate) inputting the borrower's self-reported data and credit report information into its proprietary model of borrower risk. It becomes the pre-set interest rate at which the loan is provided if originated. This is a useful feature of the institutional setting since given the fixed interest rate, the equilibrium outcome of whether the loan is provided depends directly on the supply of credit by P2P lenders.

Once submitted, the loan application is randomly allocated to one of three funding channels. The "Note Channel" allows lenders to commit to purchase all or part of the loan subject to the minimum investment of $25. Borrowers are provided with a partial funding option, which means that a loan may originate if lenders collectively commit to funding at least the specified percent of the requested amount. The current partial funding threshold is 70%. Loan applications subject to the partial funding threshold has accounted for 93.5% of all Prosper listings since the threshold was introduced in later December 2010. This is another useful feature of the institutional setting as it allows for identification using regression discontinuity design (RDD). The listing expires within 14 days if it does not receive sufficient funding unless it is withdrawn or cancelled prior to expiration.

If the application receives funding commitments above the funding threshold, the application is marked as completed[16]. The "Active Loan Channel" allows investors to purchase 100% of the loan directly from Prosper. Any loan applications that do not receive commitment within one hour are automatically reallocated to the Note Channel. The "Passive Loan Channel" reserves the loan for sale to investors who pre-committed to purchasing the loan with specific characteristics based on their lending standards and risk-return requirements. The loans in this channel automatically receive full funding. The Active and Passive Loan Channels are dominated by institutional investors and high-net-worth individuals as lenders. The Note Channel is P2P lending in its essence, although institutional investors also play a significant role in funding loan applications in the Note Channel.

When the percent funded crosses the funding threshold, Prosper starts the "pre-funding" review process. It comprises of the analysis of the borrower's risk profile, assessment of any irregularities with respect to the application or investor commitments, and verification of the accuracy of information submitted by the borrower. Prosper may cancel the loan application and all respective funding commitments in one of three cases, namely if the application contains any personally identifiable or prohibited information, if borrower-reported information cannot be verified, or if it deems that the borrower risk is materially greater than the risk reflected in the borrower rate. Borrowers may withdraw the application at any time prior to expiration and are required to do so if the information they submitted has changed. Overall, 43.20% of all applications on Prosper have been completed, 22.65% expired, 18.77% have been cancelled and 15.38% withdrawn.

If the application passes the "pre-funding" review, the loan is originated. In case of partial funding, the loan originates in the funding amount it received. Prosper restricts repeat borrowing on its platform. Borrowers are allowed to have up to two Prosper loans outstanding at any point in time and the aggregate outstanding principal should not exceed the maximum loan amount. Likewise, borrowers may not apply for an additional loan if they stop satisfying the eligibility requirements or fail to pay down the Prosper loan in full, e.g., as a result of default or personal bankruptcy. Since

[16] The loan application cannot be more than 100% funded. The application becomes completed as soon as it reaches 100% in terms of total funding commitments.

the purpose of my analysis relies on observing P2P borrowers over time, most of my empirical tests focus on repeat applicants on Prosper (further – repeat borrowers).

3 Data and Sample

This Section provides an overview of the data and the sample. I start with describing the data set and sample construction. I then proceed to the summary statistics (refer to Appendix A for detailed definitions of variables).

3.1 Sample Construction

Prosper's data set contains anonymized application-level data from November 2005 to September 2015 spanning the entire period of P2P lending in the U.S. The uniqueness of the data set is in its scope and richness. The data set contains entries on both rejected and approved loan applications, which allows avoiding selection bias conditional on applying for a Prosper loan. The data set includes a number of variables that pertain to the loan itself, such as requested amount and interest rate, and to borrower characteristics. Borrower characteristics include self-reported variables, such as income and employment, and credit bureau data that is pulled at the time of application. The minimum loan amount on Prosper is currently $2,000 and the maximum amount is $35,000. The median borrower requests $9,400 and the median originated loan is for $10,000. Loans have amortization periods of 12, 36, or 60 months. Interest rates range from as low as 5% to as high as 35% with the median interest rate on originated loans of 14.43%.

The main sample in this paper is from January 2011 to September 2015. I extend the sample back to November 2005 for placebo tests. This sample restriction stems from the use of the funding threshold in the Notes Channel introduced by Prosper in late December 2010 in my identification strategy. In addition, this restriction of the sample allows verifying that the results are not driven by the crisis period. This also rules out the effect of the auction model that Prosper had in the past on the results as the partial funding threshold was introduced by Prosper only in December 2010 after it transitioned to the lending model based on pre-set interest rates. I also restrict the sample to borrowers who have their first P2P borrowing experience after 2010.

3.2 Descriptive Statistics

A representative borrower on Prosper is a consumer with a strong borrower risk profile but high debt and lack of collateral (Table 1). The median credit score (FICO) across all loan applications is 690, which is close to the minimum eligibility requirement of 640 on Prosper but still puts the borrower into the prime category. The mean annual income of Prosper borrowers of $74,400 is more than two times higher than the per capita annual income of $30,176 in the U.S.[17]. The median annual income of Prosper borrowers is $63,600. A representative P2P borrower in the sample has been employed for 9 years and has 18 years of credit history. This suggests that she is a high-income but young individual. If most of the income is coming from self-employment or if she has recently started formal employment, she may lack documentation necessary to get a regular bank loan.

The representative borrower has a high debt burden. Her median total debt balance is $93,400, which is larger than the median household debt of $60,400 in the U.S.[18] and thus likely much higher than the debt level of a median individual in the U.S. The structure of consumer credit of the representative Prosper borrower contains a large proportion of revolving debt.[19] Seven out of eight open accounts that the P2P borrower has at the time of application are revolving accounts, including credit cards. The representative borrower utilizes her revolving accounts heavily. Her median revolver utilization is 48% and the median credit card utilization is 56%. Her median revolving balance is

[17] The reference value is based on data from the Annual Social and Economic Supplement (ASEC) to the Current Population Survey (CPS) collected by the Bureau of Labor Statistics and the U.S. Census Bureau. See http://www.census.gov/hhes/www/income/about/index.html for more details. The latest data release is for 2014.

[18] The reference values for the total level of debt and credit balances are from the Survey of Consumer Finances (SCF) collected by the Board of Governance of the Federal Reserve System. The latest data release is for 2013. See http://www.federalreserve.gov/econresdata/scf/scfindex.htm for more details. The mean and median household debt numbers in the Survey of Consumer Finances are comparable with respective values based on the Wealth and Asset Ownership data from the Survey of Income and Program Participation (SIPP) collected by the U.S. Census Bureau.

[19] Consumer credit is divided into two major types: revolving and nonrevolving. Revolving credit allows to borrow up to a prearranged limit and repay the debt in one or more installments. Credit card debt is an example of revolving credit. Nonrevolving credit consists of installment credit and mortgages. Installment credit is closed-end credit extended to consumers that is repaid on a prearranged repayment schedule. Motor vehicle loans, education loans, and personal loans are examples of installment credit. Mortgage is nonrevolving credit secured by real estate. Refer to G.19 Statistical Release, "Consumer Credit," Board of Governors of the Federal Reserve System at http://www.federalreserve.gov/releases/g19/about.htm for more details.

\$11,000[20] and her median installment balance is \$17,100, larger than the median installment balance of \$14,600 for U.S. households. A rough comparison of the revolving balance with the monthly debt payments supports the assumption that a large portion of revolving debt is rolled over to next periods rather than paid down. This explains her low median debt-to-income ratio of 0.17. The evidence above also suggests that high-interest unsecured debt comprises a large portion of total debt for the representative P2P borrower.

The median borrower on Prosper does not own a home. The mean mortgage balance of P2P borrowers is \$103,700 and the median balance is \$18,300. For comparison, the mean value of balances on mortgages and home-equity loans carried by U.S. households is \$156,400 and the median is \$116,000. This suggests that P2P borrowers lack collateral for a home-equity loan that can be used to refinance existing debt at a lower rate[21]. It may also suggest that at least some P2P borrowers are not eligible for a mortgage based on other criteria than the FICO score. The representative borrower requests \$12,000 on Prosper at the rate of 17.1%. The mean funding rate of applications is 96.6% but only 64% of applicants get P2P loans. The median borrower gets fully-funded and receives a Prosper loan. I classify 18% of borrowers as repeat borrowers, which means that they post more than one loan application on the platform. The median number of loan applications that I observe per repeat borrower is two.

I also look at three different subsamples of borrowers based on their funding status, i.e. percent of their requested loan amount funded by P2P lenders (see Table 1). I define highly-funded borrowers as borrowers whose applications were 100% funded, marginally-funded borrowers as borrowers who received funding commitments between 40% and 100% of the listed loan amount, and underfunded borrowers as the ones with percent funded of less than or equal to 40%. The choice of the lower band that is equally distanced from the partial funding threshold given the upper band of 100%

[20] For reference, the median value of credit card balances carried by households in the U.S. was \$5,700 in 2013 based on the Survey of Consumer Finances. This is not directly comparable with revolving balances as credit card debt is only one type of revolving debt.

[21] One way to consolidate debt is to take a home-equity loan from a bank. However, if borrowers attempt to consolidate their debt with banks through home-equity loans, banks can have foreclosure on the home in case of delinquency. In contrast, P2P lending in unsecured and may be preferred by borrowers, especially if they are concerned with the effect of possible liquidity shocks on their debt.

offers the convenience of the choice of RDD bandwidth up to the maximum possible bandwidth that does not include percent funded of 100%.[22] Splitting the sample into these three categories provides additional insights into how funding success correlates with borrower characteristics.

A natural question is whether percent funded is an appropriate measure of borrower credit quality and whether it measures anything else, for instance the risk-return characteristics of the offer or the degree of credit constraints. Percent funded has high negative correlation with the interest rate on P2P loans and thus captures borrower credit risk. The analysis of the descriptive statistics confirms that percent funded can discriminate between borrowers of different credit quality[23]. The median interest rate for highly-funded borrowers is 17.1% whereas it is 18.5% for marginally-funded borrowers and 23.3% for underfunded borrowers. Interestingly, the metric that is traditionally used to gauge credit quality of prospective borrowers, namely the FICO score, does not seem to discriminate well between these borrowers on its own as its binned values are comparable for the three categories of borrowers[24]. The evidence suggests that percent funded reflects borrower creditworthiness but picks up additional borrower characteristics that are not reflected in the FICO score and may not fall within the formal lending guidelines of banks. This speaks in favor of percent funded being an appropriate measure of credit quality.

Unreported regression results support the underlying assumption that the market discriminates well between borrowers of good and bad credit quality. They confirm that percent funded captures some additional borrower characteristics related to creditworthiness on top of the borrower rate or the FICO score. Conditional on the borrower rate, more creditworthy borrowers receive more funding. I

[22]The lower band for marginally-funded borrowers was chosen to allow the partial funding threshold of 70% to be the midpoint of the interval based on percent funded. The identification in a local regression discontinuity design (RDD) that I am using in further tests of the effect of financial innovation on credit-rationed borrowers is coming from a narrow bandwidth around the funding threshold. Thus, the empirical results are not sensitive to alternative definitions of the three categories of borrowers as long as the definition of marginally-funded borrowers is based on the interval that encompasses the partial funding threshold.

[23]The definition of credit quality that I use measures different grades of credit quality of most creditworthy consumers in the population as P2P lending platforms focus on prime and near-prime borrowers, i.e. borrowers with FICO score of over 640 (see "Loans that Avoid Banks? Maybe Not", The New York Times, May 3, 2014). Specifically, only borrowers with FICO scores above 640 on Prosper and above 660 on Lending Club are eligible for P2P loans.

[24]The FICO score is a coarse measure of credit quality and there is a lag in updating this measure. This may explain preference for supplementing FICO with other lending criteria.

also observe that the number of current and open credit accounts, including open revolving accounts, declines with percent funded. Consistently, I observe that underfunded borrowers have less debt and carry lower balances on credit accounts. This evidence suggests that percent funded also proxies for personal credit constraints.

4 Empirical Methodology

I use the following empirical strategy to test the effect of P2P lending on credit provided by traditional financial intermediaries. I first estimate a fixed effects model to show the impact of obtaining a P2P loan on credit outcomes for the overall sample of borrowers. I then have a closer look at the subsample of marginally-funded borrowers where I can identify the causal effect of P2P lending on credit supply and demand by consumers.

4.1 Fixed Effects Estimation

I start by estimating an OLS regression with borrower fixed effects. I treat consumer credit variables observed after each P2P loan application as outcomes and the lagged P2P loan indicator as the regressor of interest. I make use of within-borrower variation in consumer credit and compare outcomes for borrowers who receive P2P loans to outcomes for borrowers who do not. The baseline regression specification is as follows:

$$Y_{ist} = \beta \mathit{P2P\ loan}_{is,t-1} + \mathbf{X}_{ist}\zeta + \alpha_i + \gamma_s + \delta_t + u_{ist}, \tag{1}$$

where Y_{ist} is a dependent variable, such as limits on revolving accounts or credit card utilization, $\mathit{P2P\ loan}_{is,t-1}$ is the lagged indicator of an originated P2P loan, $\mathbf{X}_{ist}$ is a matrix of controls, α_i is borrower fixed effects, γ_s is state fixed effects, and δ_t is time fixed effects.

The regressor of interest $\mathit{P2P\ loan}_{is,t-1}$ is an indicator variable that takes the value of one if a P2P loan is originated on the preceding loan application and zero otherwise. It measures the marginal effect of P2P lending on access to credit and credit demanded by borrowers from traditional financial intermediaries after each P2P loan application. The median repeat borrower on Prosper's P2P lending platform submits two loan applications. In order to mitigate concerns of sample attrition, I restrict the analysis to the first and second applications. I relax this constraint in robustness checks. I also check the effect of alternative definitions of the regressor of interest and alternative specifications on the results.

I control for the credit score (FICO), income, length of employment, home ownership, and the debt-to-income ratio. I use contemporaneous controls in fixed effects regressions as they better capture the credit quality of borrowers at a particular point in time. I do not include lagged controls into the regressions as doing this substantially reduces the sample size affecting the power of estimates and does not allow to focus on outcomes after the first experience with P2P lending. In addition, some controls, such as monthly income, are very persistent so they are absorbed by fixed effects and using their lagged values instead would not help increase the precision of estimates. I use borrower fixed effects to absorb any time-invariant unobservable borrower characteristics. I use state fixed effects to control for local economic conditions and regulatory differences in consumer credit markets across states. I use time fixed effects based on the year of application to take into account the credit cycle in the economy in general. I cluster standard errors at the borrower level to take into account autocorrelation in credit decisions by borrowers.

As I discuss in the preceding section, a loan application does not result in P2P loan origination if it expires unfunded, is cancelled by Prosper, or is withdrawn by the borrower. Some of these categories may be considered problematic. Specifically, borrowers whose applications are cancelled as a result of the pre-funding review may be more prone to moral hazard or may be substantially different from other borrowers in terms of their credit risk. I explore the sensitivity of fixed effects estimates to removing cancelled applications from the analysis in robustness checks. Borrowers who withdraw their loan applications may also be different from those borrowers whose loan applications expire unfunded. If borrowers withdraw their funded loan applications because they are able to receive a loan elsewhere, e.g., from other P2P lending platforms, the results of the fixed effects regressions likely understate the effects of P2P lending on the supply and demand for credit from traditional financial intermediaries.

Given that credit constraints may be binding for certain categories of borrowers, specifically borrowers with shorter credit histories (Jappelli, 1990) and borrowers with lower FICO scores (Agarwal, Chomsisengphet, Mahoney, and Stroebel, 2016), I test the sensitivity of the effect of P2P lending on credit supply and demand to these characteristics measured *ex ante* by using interaction terms and sample splits. Specifically, I use the following specification for the interaction with the credit history:

$$Y_{ist} = \lambda \textit{Credit history} \times \textit{P2P loan}_{is,t-1} + \beta \textit{P2P loan}_{is,t-1} + \phi \textit{Credit history} + \mathbf{X}_{ist}\zeta + \alpha_i + \gamma_s + \delta_t + u_{ist}, \quad (2)$$

where Y_{ist} is a dependent variable, *Credit history* is the length of the credit history, measured in years at the first application, $\textit{P2P loan}_{is,t-1}$ is the lagged indicator of an originated P2P loan, $\mathbf{X}_{ist}$ is a matrix of controls, α_i is borrower fixed effects, γ_s is state fixed effects, and δ_t is time fixed effects.

I also split the sample based on *ex-ante* credit quality of borrowers as measured by their FICO score bin on the first application. Since financing frictions that reduce access to credit are more severe for borrowers of lower credit quality, I expect the results on the credit supply to be stronger for borrowers with lower FICO scores. Specific predictions on the impact of P2P lending on the demand for credit depend on the underlying friction that P2P lending mitigates. If the effect is driven by credit repricing, the impact should increase with the credit quality of borrowers. In contrast, if the effect is driven by reduced credit rationing, I expect the results on the demand side to be stronger for borrowers of lower credit quality.

To check the robustness of the fixed effects results, I split the sample by the time borrowers come back for another loan into three subsamples: borrowers who come back within 1 year, borrowers who come back in 1 to 2 years, and borrowers who come back after 2 years. Although I am splitting by a choice variable of borrowers, I believe that it is a reasonable robustness test for two reasons. First, since borrowers can come back to the platform at different times, I would like to compare borrowers who receive a P2P loan to borrowers who do not but come back within the same time period. Second, borrower credit quality and their credit choices may change significantly in the long run. Thus, if any effects I find persisted beyond the first year after receiving a P2P loan, they would be difficult to explain by P2P lending itself.

4.2 Endogeneity

One concern with the fixed effects estimation is potential endogeneity bias because of unobservable borrower risk. Consumer credit variables feed into Prosper's proprietary credit model and are correlated with the borrower rate. Since these variables are observed by P2P lenders when they make funding decisions, borrower characteristics may affect funding both unconditionally and conditional on the borrower rate. Funding success, in turn, affects borrowers' credit choices and may have spillover effects on traditional financial intermediaries. This creates potential simultaneity bias as unobservable borrower risk simultaneously determines whether a borrower receives a P2P loan, access to credit, and demand for credit from traditional credit intermediaries. While borrower fixed effects remove time-invariant unobservable differences in borrower risk, any such differences that are time-varying cannot be captured by fixed effects.

Thus, potential endogeneity of receiving a P2P loan and access to and credit outcomes for borrowers driven by unobservable borrower risk may impair the ability of an econometrician to determine the direction of causality between P2P lending and credit supply and demand by borrowers. I attempt to overcome this issue with regression discontinuity design (RDD).

4.3 Regression Discontinuity Design (RDD)

4.3.1 Local Fuzzy RDD

I use the setting in the Note Channel on Prosper where borrowers are offered partial funding option to identify the effect of P2P lending on access to credit and credit demanded by borrowers from traditional financial intermediaries. The funding threshold on the platform is 70%. Since some applications that cross this threshold do not result in loan origination because they are withdrawn or cancelled, I use the fuzzy RDD around percent funded of 70% as the empirical strategy to establish causality between P2P lending and credit demand and supply. I instrument loan origination with an indicator variable that switches to one after crossing the funding threshold. The forcing variable is *Percent funded*, which is the percent of the requested P2P loan amount funded by investors. I include percent funded and squared percent funded as well as splines, i.e. their interactions with the indicator for crossing the threshold, as controls in both the first-stage and second-stage regressions. The estimate from the fuzzy RDD regressions is the average treatment effect (ATE).

Including the entire spectrum of borrowers into RDD regressions may bias the estimates as borrowers of high credit quality are not comparable to borrowers of low credit quality. Since borrower risk profile is correlated with percent funded, and therefore with the above indicator, this makes borrowers at the extremes of percent funded not comparable. Therefore, I use the local RDD approach rather than the global RDD in the empirical tests. The baseline bandwidth h is 10%. Since around 67.3% of treated compliers, i.e. borrowers whose applications were funded and who receive P2P loans, fall within the 5% bandwidth and 98.8% fall within the 10% bandwidth, my choice of the 10% bandwidth seems a decent compromise in the trade-off between noise and bias. In robustness tests, however, I look at the effect of the choice of bandwidth on the empirical results.

The baseline local fuzzy RDD specification is described by the following two equation system:

$$Y_{ist} = \beta P2P\ loan_{is,t-1} + f(Distance_{is,t-1}) + Above_{is,t-1} \times f(Distance_{is,t-1}) + \gamma_s + \delta_t + \epsilon_{ist} \tag{3}$$

$$P2P\ loan_{is,t-1} = \phi Above_{is,t-1} + g(Distance_{is,t-1}) + Above_{is,t-1} \times g(Distance_{is,t-1}) + \gamma_s + \delta_t + \omega_{ist}, \tag{4}$$

where Y_{ist} is a dependent variable, $P2P\ loan_{is,t-1}$ is the lagged indicator of an originated P2P loan, $Above_{is,t-1}$ is an instrument in the form of a binary variable equal to one if $Distance_{is,t-1} \geq 0$ and $-h \leq Distance_{is,t-1} \leq h$, γ_s is state fixed effects, and δ_t is time fixed effects, *Distance* is the difference between the forcing variable (percent funded) and the discontinuity threshold, and *Distance sq.* is the squared distance from the discontinuity threshold. Equation (2) is the second stage of the RDD equation system. Equation (3) is the first stage of the RDD equation system.

Identification using RDD relies on the internal validity of this empirical strategy. The relevance condition for the instrument holds as only borrowers whose applications cross the funding threshold are given an opportunity to receive a P2P loan. This is illustrated in Figure 1. The graph exhibits a clear discontinuity around the funding threshold of 70%. The probability of receiving a P2P loan jumps by around 30% and remains strictly greater above the threshold. The relevance of the instrument can be supported statistically by looking at the estimates from the first stage of the RDD regressions. The weak instrument problem is also mitigated by the fact that loan origination is just identified.

I also argue that the instrument I use for the fuzzy RDD satisfies the exclusion restriction. Firstly, there is no reason to believe that the choice of the threshold was related to pre-existing discontinuity in the outcome variable or lack of comparability above and below the threshold. I find no evidence that the funding threshold was set by Prosper because of some prior belief about the funding probability. I further provide indirect evidence of the absence of such pre-existing discontinuity in placebo RDD estimation. Therefore, I do not expect borrower risk to jump after applications cross the funding threshold. Secondly, I observe that the density of the forcing variable is clustered just above the funding threshold (see Figure B.1 in Appendix B). However, this is problematic for inference only if there is evidence of manipulation *by borrowers* and such manipulation is *perfect*. The way P2P lending platforms operate suggests that borrowers cannot perfectly manipulate the forcing variable even if they have an incentive to do so. Any improvement in the FICO score or other variables that appear on the credit report takes time to materialize (see Keys, Mukherjee, Seru, and Vig, 2010 for a discussion) and any changes to the credit history are not seen by P2P investors after the loan application is listed until a borrower decides to submit a new application.

In order to inspect the possibility of manipulating percent funded by asking friends or relatives to fund the loan when it is close to the threshold, I manually collect data on investments from friends and family into P2P loans from Prosper's sales reports. This data is available for the sub-period starting from January 2011 when Prosper switched to pre-set interest rates to April 2013 when the whole loan program was introduced and Prosper stopped disclosing this information. The data shows that a mere 0.68% of P2P loans in this sub-period have investments from friends and family and if they do, adjusting for these investments keeps these loans above the bandwidth chosen for the RDD analysis (see Table B.1 in Appendix B for these results). This provides comfort to assume that manipulation using friends and relatives, if any, cannot substantially affect the results. Even if it is indeed possible to manipulate the threshold, the internal validity of RDD is not compromised if the manipulation is not perfect (Lee and Lemieux, 2010), i.e. the RDD is still valid if the probability of treatment is weakly greater above the funding threshold. I do not find any evidence of such perfect manipulation. The exogeneity of the funding threshold means that it assigns borrowers randomly into those who receive a P2P loan and those who do not if one looks at a narrow bandwidth around the threshold.

I do not include controls into the baseline regression specification as they are not needed if treatment is random.[25] In robustness tests, however, I check whether including controls affects the estimates. I also check whether crossing the funding threshold has any ex post impact on variables that I am using as controls. As another robustness check, I follow Lee and Lemieux (2010) and include lagged outcome variables as controls. Such specification is warranted if outcome variables are persistent, which seems to be the case for consumer credit variables of interest. I run an additional robustness test to address concerns of selection due to sample attrition. Selection due to attrition arises because fewer and fewer borrowers return to Prosper as the application number increases and outcomes for those who do not return are unobservable. I address this concern by restricting the analysis to the outcome after the first application.

4.3.2 Placebo RDD

I strengthen the internal validity of my research design by running a placebo test of the local fuzzy RDD around the 70% threshold on a subset of P2P loan applications not subject to this funding threshold. These applications may become P2P loans only if they are funded in full. If my RDD

[25] Controls are useful in truly randomized experiments only if they help make the estimates more precise by absorbing residual variation. Controls are generally not included into RDD regressions if control variables are persistent and correlated with the forcing variable in order to avoid contaminating estimation results with biases. This seems to be the case for consumer credit variables.

analysis indeed captures the effect of receiving a P2P loan rather than some spurious correlation between the loan application being funded and outcome variables, there is no reason to expect any effect of crossing the placebo funding threshold for these borrowers.

Loan applications not subject to the 70% funding threshold come from the Notes Channel. They are not subject to partial funding because of two reasons. Firstly, Prosper introduced the 70% funding threshold in late December 2010 so any loan applications before this time with funding commitments falling within the selected bandwidth are part of this subsample. Secondly, borrowers who apply for a P2P loan from Prosper from 2011 onwards may not choose the partial funding option or Prosper may decide that the borrower does not qualify for partial funding. Cases when borrowers do not choose the 70% funding threshold whenever it is available or when Prosper does not extend this choice to borrowers are very infrequent and 92.7% of observations in this subsample come from the first source, i.e. loan applications submitted before January 2011. Since this subsample captures a period before the funding threshold was introduced, looking at the outcomes for borrowers around the placebo funding threshold also allows to indirectly test whether this funding threshold was set because of some pre-existing discontinuity in borrower characteristics around the 70% funding.

In order to match the fuzzy RDD setting above, I set the placebo loan origination variable to one for expired loan applications and zero for borrowers with withdrawn or cancelled applications. Thus, the regression specification is described by the following two equation system:

$$Y_{ist} = \beta P2P\ loan_{is,t-1}(placebo) + f(Distance_{is,t-1}) + Above_{is,t-1} \times f(Distance_{is,t-1}) + \gamma_s + \delta_t + \epsilon_{ist}$$
$$P2P\ loan_{is,t-1}(placebo) = \phi Above_{is,t-1} + g(Distance_{is,t-1}) + Above_{is,t-1} \times g(Distance_{is,t-1}) + \gamma_s + \delta_t + \omega_{ist},$$

where Y_{ist} is a dependent variable, $Above_{is,t-1}$ is an instrument in the form of a binary variable equal to one if $Distance_{is,t-1} \geq 0$ and $-h \leq Distance_{is,t-1} \leq h$. The baseline bandwidth h is 10%. The dependent variable $P2P\ loan_{is,t-1}(placebo)$ is the lagged indicator of the placebo P2P loan origination which equals to 1 if the loan application was above the threshold and expired and 0 if the loan application was cancelled, withdrawn or was below the threshold and expired unfunded.

The instrument $Above_{t-1}$ is an indicator of the funding commitments being at least 70% of the requested loan amount. *Distance* is the difference between the forcing variable (percent funded) and the discontinuity threshold. *Distance sq.* is the squared distance from the discontinuity threshold.

5 Empirical Results: External Access to Credit

My first set of empirical results shows the impact of P2P lending on access to credit provided by traditional credit intermediaries. I look at how receiving a P2P loan from fintech companies affects limits on revolving accounts and the number of revolving accounts held by borrowers. Consistent with my methodological approach, I first discuss the results of fixed effects regressions, including sample splits, and then proceed to discussing the results of the RDD estimation.

5.1 Fixed Effects Regressions

In fixed effects regressions, I look at the effect of P2P lending on external access to credit by borrowers using the panel character of the data. Table 2 presents the empirical results from the fixed effects estimation. I measure the supply of credit to borrowers from traditional credit intermediaries with limits on revolving accounts and the number of these accounts. P2P loans are amortizing loans that are treated as installment credit so they are not part of revolving debt. In contrast to total debt, which is the equilibrium result, revolver limits are a more direct measure of external credit supply to borrowers. I find that P2P lending is associated with an increase in revolver limits for borrowers who receive P2P loans compared to borrowers who do not. The increase is at least $990 or 2.5% relative to the mean revolver limit on the first application. The number of revolving accounts goes up as a result of P2P lending as well, although the increase is smaller than the increase in revolver limits. P2P lending is associated with the increase in the number of revolving accounts by 1.3% relative to the sample mean on the first application. These results, however, may underestimate the effect of P2P lending on access to credit if some borrowers with rejected loan applications from Prosper are able to obtain credit from other P2P lenders, e.g., from Lending Club.

Technological innovation in the way borrowers are screened and loans are funded that improves the information environment should primarily benefit borrowers who were credit rationed by traditional financial intermediaries before but succeed in obtaining a P2P loan. These borrowers could not have otherwise obtained a loan even if they were ready to pay high interest. This predicts that P2P lending leads to more credit expansion for borrowers with shorter credit histories and borrowers of lower credit quality. I find that the effect of P2P lending on credit limits is sensitive to the length of credit history as expected (Table 3). Borrowers with shorter credit histories who are expected to be more credit constrained enjoy a larger increase in credit limits and the number of revolving accounts.

I provide the results of the sample splits by *ex ante* credit score in Table 4. Consistently, I find that the increase in revolver limits and revolving accounts is coming from borrowers with lower FICO scores. The results support the hypothesis that financial innovation elevates credit constraints for marginally creditworthy borrowers by providing credit to those borrowers who were credit-rationed by traditional financial intermediaries and acting as a certification device. The evidence that traditional credit intermediaries increase access to credit for borrowers who get loans from fintech companies is consistent with the theory of information cascades (e.g., Welch, 1992; Banerjee, 1992; Bikhchandani, Hirshleifer and Welch, 1992). These findings suggest that traditional financial intermediaries extract useful information from P2P lending and incorporate this information in their credit decisions.

5.2 Regression Discontinuity Design

To set the stage for the RDD analysis, I look at conditional expectations of revolver limits and the number of revolving accounts. I plot these outcome variables against the lagged percent of the P2P loan application funded by investors in Figure 2. The graph shows a clear discontinuity in all of these variables around the 70% funding threshold and suggest that P2P lending causes a significant increase in revolver limits and the number of revolving accounts for borrowers. Two things should be noted about these graphs. First, all borrowers below the threshold do not receive P2P loans while some, but not all borrowers above the threshold do. Thus, the graphical analysis likely underestimates the effect of P2P lending on borrowers who do receive P2P loans. Second, I do not condition on time or state where the borrower resides in constructing these graphs. Conditioning on these variables may result in more precise estimates.

I provide the results of the local fuzzy RDD analysis in Table 5. Since I do not include borrower fixed effects into the estimation, the RDD results are coming out of the cross section. I use the bandwidth of 10% in the baseline specification.[26] The first-stage regressions in Table 5-A show that the instrument is strong. Standard errors in the first-stage estimates are small and the F-statistic is above 10 (see Stock, Wright, and Yogo, 2002). The Cragg-Donald Wald F statistic and the Kleibergen-Paap Wald F statistic are both above the Stock-Yogo critical value of 16.38 so the weak instrument hypothesis can be rejected (see Table 5-A). Thus, the instrument is relevant as crossing the funding threshold positively and statistically significantly affects the probability of loan origination.

The results of estimating the second stage of the local fuzzy RDD regressions are presented in Table 5-B. I use both linear and quadratic specifications with little effect on the results. The empirical results from the local fuzzy RDD support the main conclusions from the fixed effects model and the results are stronger economically. I find that marginally-funded borrowers who are granted a P2P loan enjoy higher credit limits on their revolving accounts and have more revolving accounts with traditional financial intermediaries. Specifically, obtaining a P2P loan induces traditional financial intermediaries to increase credit limits on revolving accounts by at least \$51,000, which is a 105.3% increase compared to the mean credit limit for marginally-funded borrowers. Importantly, the results remain qualitatively and quantitatively similar when I include lagged outcome variables as controls, thus making use of the panel character of the data I have (Table B.6 in Appendix B). The difference in economic magnitudes may be due to RDD estimating the local treatment effect, which may be weaker for borrowers outside of the narrow bandwidth that I use for this analysis. I also observe that marginal borrowers who receive P2P loans get more mortgages so the increase in credit limits may be larger because of additional home equity lines of credit they obtain. These results show that banks respond to P2P lending by increasing the supply of credit to borrowers who receive P2P loans.

[26] I also looked at pairwise correlations between percent funded and contemporaneous consumer credit variables as a rule of thumb to validate the choice of the bandwidth and the respective correlations are very small and significant only for the maximum bandwidth.

5.3 Robustness

I do several robustness checks of the main set of results. My results from the fixed effects estimation are not driven by the choice of fixed effects and level of clustering or the method of dealing with outliers (winsorization or trimming levels). The results are robust to excluding any cancelled applications or pairs of observations with stale credit reports from the sample (Table B.2). I establish that the results are robust to alternative definitions of the regressor of interest. I use the number of prior Prosper loans instead of loan origination as a robustness check. The regressor takes the initial value of zero and increases by one after each P2P loan is obtained. It measures the strength of the effect in subsequent periods and the strength of the effect with more P2P loans. The results are economically and statistically comparable to the ones obtained in the main specification. This measure, however, seems inferior to loan origination because of sample attrition. The results on external access to credit come from borrowers who come back for another loans within one year of the first applciation, as expected (Table B.3).

I confirm the internal validity of the local fuzzy RDD analysis by running a placebo test on the subsample of borrowers not subject to the 70% funding threshold. The estimation results are presented in Table B.4. The placebo test shows that there is no effect from placebo treatment on the total debt, limits on revolving accounts, or the number of revolving accounts.

I run a number of additional robustness tests to address concerns that the empirical results from the RDD analysis may be affected by my empirical choices. I check that the results are not driven by the choice of bandwidth around the discontinuity threshold and regression specification (inclusion of higher-order polynomials, splines). The results are robust to the choice of bandwidth, namely 5%, 10%, 15%, and 20% (Table B.5).[27] The estimates become less significant with narrower bandwidths and economically weaker with wider bandwidths consistent with the lower precision of

[27] I do not use optimal bandwidth estimators because of the sample size. Optimal bandwidth estimators, such as Silverman's normal bandwidth reference rule, Haerdle's better rule of thumb, Silverman bandwidth estimator for normal kernel, and Scott's (Gaussian) kernel oversmoothed bandwidth, give a very narrow bandwidth because of clustering of observations around the funding threshold. Since the resulting samples are relatively small, I lack statistical power to get meaningful estimates.

estimates based on smaller samples and larger biases when observations further from the threshold are included. The results remain qualitatively unchanged.

I follow Lee and Lemieux (2010) and include lagged outcome variables as controls as is it reasonable to expect that the outcome variables, specifically credit limits and the number of credit accounts, are highly persistent across time. The results remain unchanged (see Table B.6). When I restrict the analysis to outcomes after the first application, as in the fixed effects estimation, the results still hold (Table B.7). I do not see any effect of crossing the threshold on ex post controls that I use in the fixed effects regressions, except for income (Tables B.8 and B.9). When I condition on the natural logarithm of income in my RDD analysis, the results hold. I also check if the *ex ante* FICO score jumps around the threshold, and I find no evidence of such a jump (see Figure B.2).

6 Empirical Results: Credit Demand and Delinquencies

This section provides the results of fixed effects and RDD regressions where dependent variables proxy for credit demanded by borrowers from traditional financial intermediaries and default probability.

6.1 Fixed Effects Regressions

The results of fixed effects regressions of the impact of P2P lending on credit demand by borrowers are presented in Table 6. I find that P2P lending is associated with lower revolving balances and lower utilization of credit by borrowers. Revolving balances decrease by 7.7% for borrowers who receive P2P loans compared to borrowers whose applications are rejected. I measure the decrease relative to the sample mean on the first application. I then look at utilization of revolving credit and utilization of credit cards as one specific type of revolving accounts. Revolver utilization is the ratio of credit balances to credit limits on revolving accounts. This means that any effect of financial innovation on revolver utilization may either come from its effect on credit limits, which is the supply-side effect, or its effect on credit balances, which is the demand-side effect. Given the empirical evidence on the increase in revolver limits in the preceding section and the evidence on the decrease in credit balances, the decrease in revolver utilization should be higher compared to the decrease in the revolving debt level. I find that P2P lending is associated with the decrease in revolver utilization of 5.0 percentage points. The effect is economically significant and translates into a decrease of 10.3% relative to the mean on the first application. This evidence suggests that the decrease in utilization of revolving debt is driven by debt repayment rather than just the increase in credit supply. The effect on credit card utilization is comparable in magnitude. P2P lending is associated with a decrease in credit card utilization by 5.9 percentage points, a decrease of 10.8% relative to the mean. This evidence suggests that borrowers may use proceeds from P2P loans to consolidate their debt and prepay their high interest credit card debt.

Table 7 provides subsample analysis for borrowers of different credit quality measured by their *ex ante* FICO score. The results suggest that the effects of P2P lending on revolving balances are stronger for borrowers of higher credit quality. These results speak in support of the financial innovation inducing borrowers to substitute P2P lending for debt from traditional credit intermediaries as a result of credit repricing. The evidence suggests that borrowers of higher credit quality pay down more of their expensive revolving debt from proceeds from P2P loans.

Overall, the findings from the fixed effects estimation suggest that the proceeds from P2P loans are primarily used to pay down more expensive revolving debt and increase short-term liquidity of borrowers of high credit quality. It is also worth noting that not all proceeds from P2P loans seem to be used to repay revolving debt and may be consumed or invested. The evidence suggests that repricing of consumer debt due to financial innovation in lending results in a decrease in consumer debt, primarily revolving debt, held at traditional financial intermediaries.

6.2 Regression Discontinuity Design

Figure 3 illustrates the effect of getting a P2P loan on revolving balances, revolver utilization, and credit card utilization. The graphs present the expectation of these variables conditional on the percent funded. However, I do not condition on the differences in economic conditions across states or time. The evidence differs from the results of the fixed effects estimation. There is a visible jump in revolving balances and utilization ratios around the 70% funding threshold.

The results of the local fuzzy RDD regressions are presented in Table 8. I find that marginally-funded borrowers increase balances on revolving accounts by $29,300 as a result of P2P lending, which constitutes an increase of 137.9% relative to the mean revolving balance on the first application for this category of borrowers. This increase in credit balances over and above the increase in credit limits is reflected in the increased utilization of revolving accounts. Revolver utilization is higher by at least 24.0 percentage points after a P2P loan, an increase of 51.2% relative to the mean, and bank card utilization increases by at least 30.0 percentage points, an increase of 60.4% relative to mean bank card utilization respectively. This difference in the empirical results is likely due to these borrowers being of lower credit quality and likely more credit-constrained than other borrowers in the sample. Given the results of the effect of increased credit limits on credit choices of highly-funded borrowers in the preceding section, this evidence suggests that there are decreasing marginal returns to increasing credit supply to creditworthy borrowers as a response to financial innovation. This strategy seems to work well for only those consumers who were credit-constrained prior to getting a P2P loan.

I attribute the effect of increased revolving and total debt levels of marginally-funded borrowers to their personal finances moving towards optimal debt levels. These borrowers are likely financially constrained and would have cut down consumption absent P2P lending. The preference for liquidity made these borrowers keep some portion of their available credit unutilized[28] making them worse off consumption-wise compared to their optimal consumption smoothing over time. P2P lending mitigates credit constraints for this category of borrowers by providing loans and increasing credit supply from traditional financial intermediaries. This induces them to consume more while sustaining their preferred liquidity levels, which is reflected in higher utilization ratios and higher credit balances.

An alternative explanation may be that marginally-funded borrowers are more prone to moral hazard and overborrowing after obtaining a P2P loan. The overborrowing problem is driven by time-inconsistent preferences in the form of hyperbolic discounting and is more pronounced among

[28]Similarly to underutilization of credit capacity, the option to roll over credit card debt may act as an insurance against liquidity shocks for consumers.

consumers with personal financing constraints (Laibson, 1997). It is possible that borrowers of marginal credit quality use extended credit supply to consume more than optimal. If moral hazard is negatively related to the credit quality of borrowers, this category of borrowers may be more subject to temptation to consume out of the P2P loan rather than use it to consolidate existing debt. Increase in utilization of revolving accounts after obtaining a P2P loan over an increase in credit limits by banks may be interpreted as evidence of overborrowing[29]. This view is also expressed in Zhu, Dholakia, Chen, and Algesheimer (2012) who explore whether participating in online lending alters financial decision-making by changing risk attitudes based on field and laboratory studies. They find that participation in an online community increases people's risk-seeking tendencies in their financial decisions and behaviors if they have strong ties with other community members. Absent an identifiable benchmark for the optimal utilization ratio and credit balance amounts, it is hard to rule out this alternative explanation. I address it in the next subsection by examining the total debt and delinquencies.

6.3 Delinquencies

Financial innovation may have positive consequences for borrowers if refinancing of expensive credit from P2P loans leads to less delinquencies and personal bankruptcies, despite possibly higher total debt. In contrast, if P2P lending offers a new way for financial institutions to take advantage of behavioral biases in decision-making, I expect to see higher total debt and higher delinquencies.

The results of fixed effects regressions with the total debt and the probability of delinquency as the dependent variables are presented in Table 10. I find that the total debt of borrowers who receive P2P loans is at least 4.5% higher than the total debt of borrowers whose applications are rejected. The increase in the total debt despite the decrease in the revolving balance suggests that some creditworthy borrowers who found it too expensive to take a loan at high interest rates prevailing before this financial technology innovation may now choose to take on more debt as the benefits

[29] Overborrowing may have a detrimental effect on traditional credit intermediaries. For instance, Bizer and DeMarzo (1992) show that sequential lending imposes an externality on debt from existing lenders as the probability of repayment of prior loans decreases in the presence of moral hazard when consumers are more prone to overborrowing.

outweigh the costs. However, the estimation results of fixed effects regressions of the probability of delinquency on P2P loan origination does not show any association between P2P lending and delinquencies. Although the respective coefficient is negative, it is only marginally statistically significant and is not robust across specifications.

Figure 4 plots the expectation of the total debt and the probability of delinquency conditional on the percent funded. The graph shows a jump in the total debt above the funding threshold but I see no effect of P2P lending on the default probability of borrowers. The results of the local fuzzy RDD regression of the total debt and delinquencies are presented in Table 11. I find that the total debt of marginally-funded borrowers increases by 82.3% as a result of P2P lending. However, the increased access to credit and higher total debt as a result of P2P lending do not lead to higher delinquency rates. Thus, my findings are inconsistent with overborrowing.

6.4 Robustness

The results of the fixed effects regressions are robust to alternative sample restrictions and definitions of the regressor of interest (Table B.10 in Appendix B). Table B.11 splits the sample into borrowers who come back within 1 years, 1-2 years, and more than 2 years. As expected, the results on credit demand come from borrowers who I can observe within a year from the first P2P loan application. I find no effect of P2P lending on credit demand by consumers from traditional financial intermediaries or their default probability in placebo RDD estimation (Table B.12). The RDD results are robust to the variation in bandwidth (Table B.13). In unreported tests, I also restrict the sample to the outcome after the first application and the main findings hold.

7 External Validity

7.1 Selection on repeat borrowers

The identification of the effect of P2P lending on borrowers relies on observing applicants for P2P loans over time. I cannot observe the outcome of receiving a P2P loan unless borrowers apply for a loan one more time, this paper focuses on repeat borrowers. One of the potential concerns of the above analysis is that the results may be driven by self-selection of borrowers into repeat borrowers. While returning to Prosper for loans is restricted by the platform as mentioned in the discussion of the institutional details, applicants may choose whether to return or not. The propensity to become a repeat borrower may be higher for more creditworthy borrowers or it may be the case that only borrowers who improve their creditworthiness return to the platform in expectation of getting another P2P loan. If this case, I would overestimate the effect of P2P lending on external access to credit and credit demand by borrowers. In extreme cases, this self-selection bias may lead to a change in the sign of coefficients of interest in regressions. This would make the results difficult to interpret as it would be unclear whether they are due to hypothesized relationships or due to sample attrition.

I show that the above is not the case by comparing characteristics of repeat versus one-time borrowers on their first P2P loan application. The comparison of borrower characteristics shows that one-time borrowers appear more creditworthy than repeat borrowers. One-time borrowers have higher FICO scores, a more solid credit profile, and more debt capacity. They are more likely to have collateral. They also look less credit-constrained. One-time borrowers enjoy a lower borrower rate and request higher loan amounts. The regressions of the repeat borrower propensity are presented in Table 11. This evidence suggests that the self-selection bias, if any, works against finding the results in the preceding sections and may lead to underestimation of the results on external access to credit.

Selection on repeat borrowers is more relevant to fixed effects estimation. However, this selection may be a problem for RDD analysis if the probability of repeat application and the resulting sample attrition are different above and below the discontinuity threshold. I mitigate this concern by redoing the analysis on a subsample of borrowers where the probability to be a repeat borrower is the same above and below the funding threshold, namely borrowers with high debt-to-income ratios. I look at these debt-laden borrowers as they are unlikely to get a loan elsewhere. Specifically, I check that Prosper's main competitor in the P2P lending market, Lending Club, does not fund loan applications of borrowers with debt-to-income ratios exceeding 0.4. I also verify that these borrowers do not exhibit any differences in the probability of returning to Prosper below and above the threshold. These untabulated tests show that the empirical results remain qualitatively unchanged when the analysis is restricted to the subsample of borrowers with high debt-to-income ratios.

7.2 Generalizability

I would also like to briefly touch upon the generalizability of the analysis. Since only borrowers with FICO scores above 640 can obtain P2P loans, the effects I measure are for the highest grades of borrowers and may not extrapolate to certain classes of consumers, such as the poor or the young. There is a vast literature, however, that studies the credit behavior and credit availability for highly risky consumers (e.g., see Morse, 2011 for the effect of payday loans on borrowers and Banerjee and Mullainathan, 2010 for the effect of temptations on demand for credit by the poor). As only consumers with bank accounts are eligible to apply for P2P loans, I thus cannot speak to the effect of financial innovation in lending on unbanked consumers.

I also do not identify the effect of P2P lending on those borrowers who did not apply for a P2P loan. Since the data I use is anonymized, I cannot match it to any other borrower-specific data to explore the effect of P2P lending on these borrowers.

8 Conclusions

This paper studies the impact of financial innovation in the form of P2P lending on the supply of credit by traditional financial intermediaries and on the demand for credit by borrowers. I present empirical evidence consistent with the role of innovation in reducing imperfections in the consumer credit market by repricing credit and mitigating credit rationing. On the credit supply side, I find that fintech innovation can help reduce credit constraintes as traditional financial intermediaries increase the supply of credit to borrowers who get loans from fintech companies. On the credit demand side, I find that borrowers of high credit quality reduce utilization of revolving accounts they hold with traditional financial intermediaries after getting a P2P loan. In contrast, marginally-funded borrowers increase utilization of their revolving accounts as a result of P2P lending. This increase stems from the increase in credit balances over and above the increase in credit limits. I do not find any increase in delinquencies. The effects I estimate, however, are for consumers with FICO scores of above 640 and may not generalize to other categories of borrowers, such as consumers of very low credit quality, the poor or the young. I also cannot speak to the effect of financial technology innovation on unbanked consumers.

Although the question of how financial innovation affects banks remains open, the results of this paper suggest that both the structure of banks' revenues and balance sheets may be affected by P2P lending. The findings on debt refinancing suggest that switching to P2P lending platforms induced by financial innovation may result in a new steady state where borrowers of higher credit quality sort into these innovative lending platforms while less creditworthy borrowers remain locked in with their incumbent credit institutions (as in Broecher, 1990). This may result in redistribution of business away from incumbent financial intermediaries in favor of P2P lending platforms and have negative implications for the credit risk in the banking sector, which is an interesting avenue for future research. The results have important policy implications for traditional financial intermediaries. The evidence presented in this paper suggests that banks should invest more into finding a better way of segmenting customers and elaborating more fine-tuned responses to financial innovation in lending.

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Figures and Tables

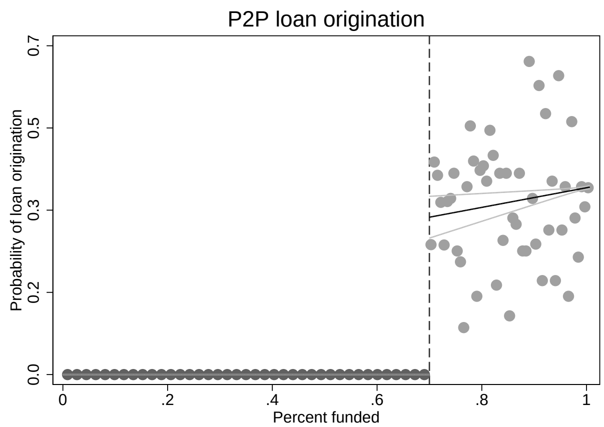

Figure 1: Discontinuity in Probability of P2P Loan Origination

This graph presents the probability of P2P loan origination as a function of the percent of the loan amount requested by the borrower funded by P2P loan investors. The binned averages represent the conditional expectation of P2P loan origination. *Percent funded* is the percent of the listing funded by Prosper investors. The straight lines are fitted values of the probability of loan origination allowing for different linear models to be estimated below and above the threshold. The light gray lines are 99% confidence intervals.

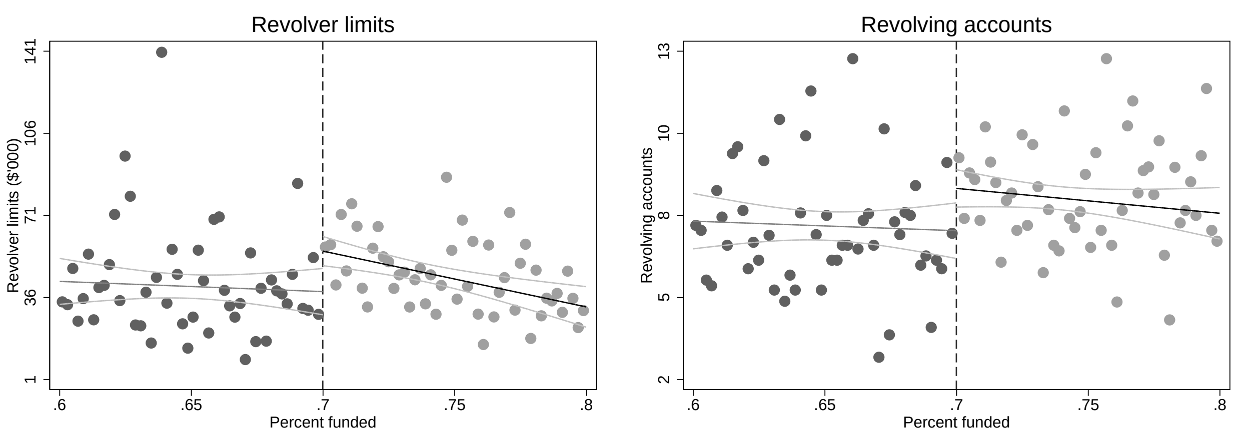

Figure 2: Conditional Expectation of External Access to Credit

This graph illustrates the effect of crossing the 70% funding threshold on access to credit by borrowers from traditional financial intermediaries. The baseline bandwidth is 10%. The binned averages represent the conditional expectation of revolver limits and the number of revolving accounts. *Percent funded* is the percent of the listing funded by Prosper investors. *Revolver limits* is the total credit limit on revolving accounts. *Revolving accounts* is the number of open revolving accounts. All outcome variables are winsorized at the 1^{st} and the 99^{th} percentiles. The straight lines are fitted values. The light gray lines are 99% confidence intervals.

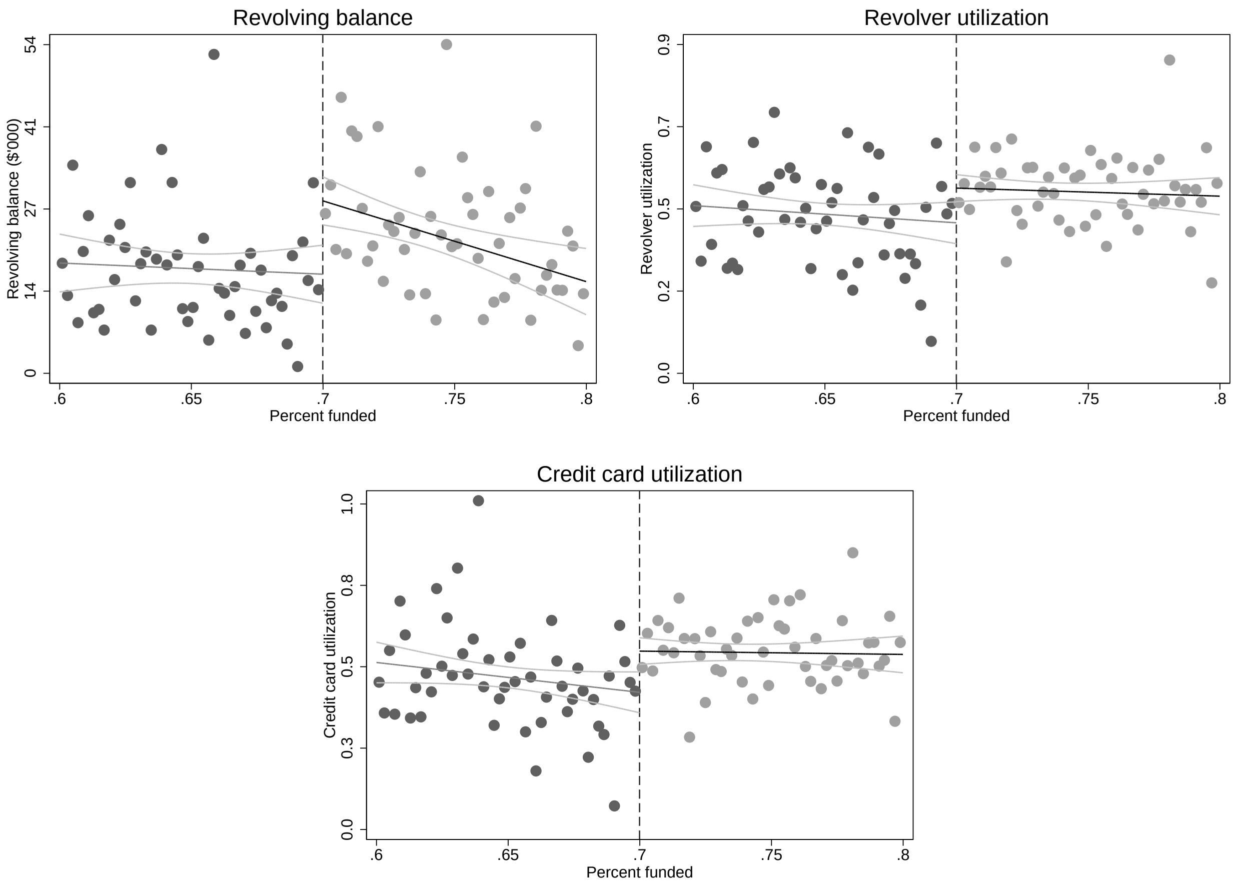

Figure 3: Conditional Expectation of Credit Demand by Borrowers

This graph illustrates the effect of crossing the 70% funding threshold on credit demand by borrowers from traditional financial intermediaries. The baseline bandwidth is 10%. The binned averages represent the conditional expectation of revolving balances, revolver utilization, and credit card utilization. *Percent funded* is the percent of the listing funded by Prosper investors. *Revolving balance* is the total balance on revolving accounts. *Revolver utilization* is the ratio of balances to limits on revolving accounts. *Credit card utilization* is the ratio of balances to limits on bank card accounts. All outcome variables are winsorized at the 1^{st} and the 99^{th} percentiles. The straight lines are fitted values. The light gray lines are 99% confidence intervals.

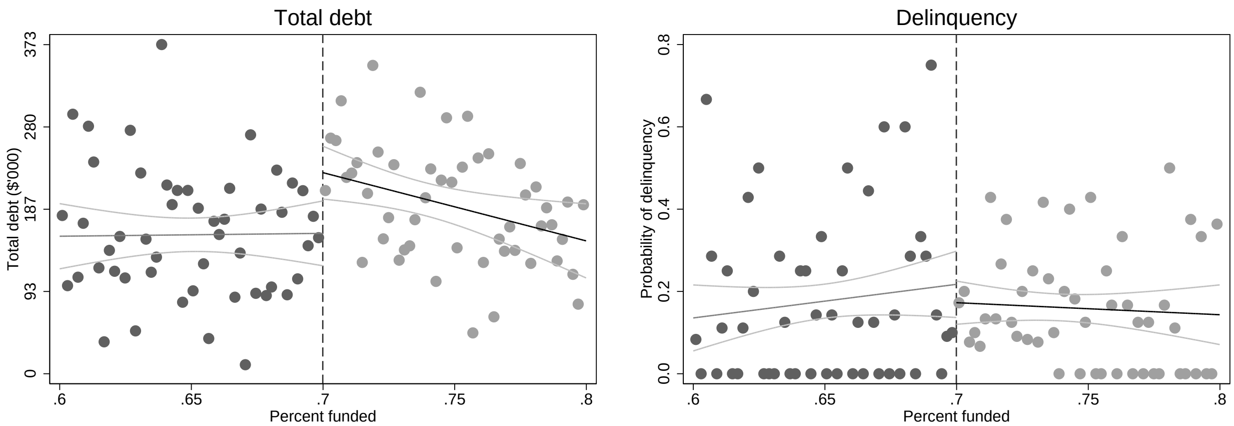

Figure 4: Conditional Expectation of External Access to Credit

This graph illustrates the effect of crossing the 70% funding threshold on the total debt and the probability of delinquency. The baseline bandwidth is 10%. The binned averages represent the conditional expectation of the total debt and delinquencies. *Percent funded* is the percent of the listing funded by Prosper investors. *Total debt* is the total balance on all credit accounts. *Delinquency* is an indicator of a delinquent borrower. *Total debt* is winsorized at the 1^{st} and the 99^{th} percentiles. The straight lines are fitted values. The light gray lines are 99% confidence intervals.

Table 1-A: Summary Statistics – Borrower FICO Score

This table provides the frequencies of FICO score bins for all P2P loan applications and by three different categories of applications based on their funding status. *FICO* [†] is a bin of the FICO classic score, where the † symbol denotes the range of the bin.

	All applicants		Highly-funded (% funded = 100%)		Marginal (40% ≤ % funded < 100%)		Underfunded (% funded < 40%)	
	N	%	N	%	N	%	N	%
FICO [<640]	640	0.16	585	0.15	7	0.29	48	0.93
FICO [640–659]	48,179	11.84	47,550	11.91	140	5.72	488	9.42
FICO [660–679]	89,903	22.09	88,683	22.20	321	13.12	898	17.33
FICO [680–699]	88,530	21.75	86,962	21.77	520	21.26	1,047	20.21
FICO [700–719]	73,241	17.99	71,878	18.00	442	18.07	920	17.76
FICO [720–739]	49,466	12.15	48,407	12.12	361	14.76	697	13.45
FICO [740–759]	26,274	6.45	25,576	6.40	254	10.38	444	8.57
FICO [760–779]	14,336	3.52	13,904	3.48	163	6.66	269	5.19
FICO [780–799]	8,352	2.05	8,076	2.02	101	4.13	175	3.38
FICO [800–819]	5,041	1.24	4,849	1.21	86	3.52	106	2.05
FICO [820–850]	3,073	0.75	2,933	0.73	51	2.09	89	1.72
Total	407,035	100.00	399,403	100.00	2,446	100.00	5,181	100.00

Table 1-B: Summary Statistics – Borrower Characteristics

This table provides the descriptive statistics of borrower characteristics. *Listing amount* is the requested P2P loan amount. *Interest rate (APR)* is the interest rate on the loan plus fees. *Percent funded* is the percent of the requested P2P loan amount funded by investors. *P2P loan* is an indicator of the originated P2P loan. *Repeat borrower* is an indicator of repeat P2P loan applicant. *Debt-to-income* is the ratio of monthly debt to monthly income. *Monthly income* is the monthly income. *Employment* is the length of employment. *Credit history* is the length of the credit history. *Home owner* is an indicator of home ownership. *Current accounts* is the number of accounts held within the last 6 months. *Open accounts* is the number of current accounts that are still open. *Revolving accounts* is the number of open revolving accounts. *Credit card utilization* is the ratio of balances to limits on bank card accounts. *Revolver utilization* is the ratio of balances to limits on revolving accounts. *Revolver limits* is the total credit limit on revolving accounts. *Revolving balance* is the total balance on revolving accounts. *Installment balance* is the total balance on installment accounts. *Mortgage balance* is the total balance on real estate accounts. *Total debt* is the total balance on all credit accounts. *Delinquency* is an indicator of a delinquent borrower. All continuous variables are winsorized at the 1^{st} and the 99^{th} percentiles.

	All borrowers (N=445,340)					Highly-funded (N=399,403)	Marginal (N=2,446)	Underfunded (N=5,181)
	Mean	SD	Median	Min	Max	Median	Median	Median
Panel A: Peer-to-peer loan application								
Listing amount ($'000)	13.2	8.0	12.0	2.0	35.0	12.0	12.5	10.0
Interest rate (APR)	18.3%	6.6%	17.1%	6.4%	36.0%	17.1%	18.5%	23.3%
Percent funded	96.6%	16.6%	100.0%	0%	100.0%	100.0%	70.0%	4.2%
P2P loan (1/0)	0.64	0.48	1	0	1	1	0	0
Repeat borrower (1/0)	0.18	0.38	0	0	1	0	0	0
Panel B: Borrower risk profile								
Debt-to-income	18.1%	12.7%	16.4%	0%	279.3%	16.5%	13.1%	13.3%
Monthly income ($'000)	6.2	3.7	5.3	0	21.8	5.3	5.5	5.0
Employment (years)	8.9	8.4	6.5	0	35.9	6.5	6.1	5.3
Credit history (years)	18.1	8.3	17.0	1.8	41.2	17.0	17.4	16.3
Home owner (1/0)	0.48	0.50	0	0	1	0	1	0
Panel C: Consumer credit variables								
Current accounts	11	5	10	0	29	10	10	9
Open accounts	10	5	9	1	25	9	8	8
Revolving accounts	8	4	7	0	23	7	7	6
Credit card utilization	54.5%	26.9%	56.0%	0%	122.0%	57.0%	47.0%	47.0%
Revolver utilization	48.6%	23.9%	48.0%	0%	100.0%	49.0%	42.0%	43.0%
Revolver limits ($'000)	39.1	40.1	26.1	0	248.8	26.1	30.1	24.7
Revolving balance ($'000)	18.7	24.0	11.0	0	159.2	11.0	10.6	8.7
Installment balance ($'000)	26.7	32.4	17.1	0	179.0	17.2	14.1	14.9
Mortgage balance ($'000)	103.7	142.3	18.3	0	713.6	20.2	43.6	0.0
Total debt ($'000)	151.3	162.4	93.4	0.8	851.1	93.9	101.7	80.3
Delinquency (1/0)	0.16	0.37	0	0	1	0	0	0

Table 2: P2P Lending and External Access to Credit

This table presents the results of OLS regressions of variables related to credit access from traditional financial intermediaries on receiving a P2P loan and borrower characteristics. The analysis is restricted to outcomes after the first application. The regression specification is as follows:

$$Y_{ist} = \beta P2P\ loan_{is,t-1} + \mathbf{X}_{ist}\zeta + \alpha_i + \gamma_s + \delta_t + u_{ist},$$

where Y_{ist} is a dependent variable and $\mathbf{X}_{ist}$ is a matrix of controls. The dependent variable *Revolver limits* is the total credit limit on revolving accounts. The dependent variable *Revolving accounts* is the number of open revolving accounts. The regressor of interest *P2P loan*$_{t-1}$ is the lagged indicator of an originated P2P loan. The economic magnitude of the coefficient of is measured relative to the mean level of the respective dependent variable on previous P2P loan application. *FICO* [†] is an indicator for a FICO score bin, where the † symbol denotes the range of the bin. *Log (income)* is the natural logarithm of monthly income, measured in thousands. *Log (employed)* is the natural logarithm of length of employment, measured in years. *Home owner* is an indicator of home ownership. *Debt-to-income* is the ratio of monthly debt to monthly income. All continuous variables are winsorized at the 1^{st} and the 99^{th} percentiles. The estimates of the intercept and fixed effects are omitted for brevity. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. T-statistics are presented in parentheses.

Dependent variable:	Revolver limits ($'000)			Revolving accounts		
	(1)	(2)	(3)	(1)	(2)	(3)
P2P loan$_{t-1}$	3.14***	1.00***	0.99***	0.50***	0.11***	0.11***
	(16.27)	(4.74)	(4.69)	(24.14)	(4.86)	(4.85)
Economic magnitude	*8.0%*	*2.6%*	*2.5%*	*6.1%*	*1.3%*	*1.3%*
FICO [640–659]	2.18	1.94	2.08	0.67***	0.46**	0.45**
	(0.83)	(0.74)	(0.80)	(3.15)	(2.09)	(2.07)
FICO [660–679]	2.07	1.82	1.96	0.85***	0.64***	0.63***
	(0.78)	(0.69)	(0.74)	(3.99)	(2.92)	(2.90)
FICO [680–699]	2.72	2.40	2.55	0.94***	0.71***	0.71***
	(1.02)	(0.90)	(0.96)	(4.36)	(3.24)	(3.22)
FICO [700–719]	2.96	2.62	2.77	0.89***	0.66***	0.65***
	(1.11)	(0.99)	(1.04)	(4.11)	(2.99)	(2.97)
FICO [720–739]	3.11	2.77	2.93	0.81***	0.58***	0.58***
	(1.16)	(1.04)	(1.10)	(3.74)	(2.64)	(2.63)
FICO [740–759]	3.83	3.49	3.64	0.79***	0.56**	0.56**
	(1.42)	(1.30)	(1.35)	(3.61)	(2.51)	(2.50)
FICO [760–779]	3.31	2.85	3.03	0.71***	0.46**	0.46**
	(1.22)	(1.05)	(1.12)	(3.21)	(2.04)	(2.03)
FICO [780–799]	2.33	1.85	2.06	0.52**	0.27	0.27
	(0.85)	(0.67)	(0.75)	(2.32)	(1.17)	(1.17)
FICO [800–819]	-1.11	-1.69	-1.45	0.38	0.10	0.10
	(-0.39)	(-0.60)	(-0.51)	(1.63)	(0.43)	(0.45)
FICO [820–850]	-5.65*	-6.22**	-6.02*	0.087	-0.18	-0.18
	(-1.84)	(-2.02)	(-1.95)	(0.36)	(-0.74)	(-0.74)
Log (income)	4.06***	3.73***	3.72***	0.60***	0.53***	0.53***
	(11.40)	(10.77)	(10.89)	(14.19)	(13.63)	(13.63)
Log (employed)	0.28**	0.15	0.12	0.046***	0.022*	0.021
	(2.20)	(1.19)	(0.99)	(3.47)	(1.72)	(1.64)
Home owner	1.83***	1.76***	1.75***	0.22***	0.20***	0.20***
	(2.97)	(2.85)	(2.82)	(4.38)	(4.05)	(4.01)
Debt-to-income	22.8***	20.6***	20.6***	3.26***	2.85***	2.85***
	(10.38)	(9.77)	(9.79)	(11.39)	(10.93)	(10.93)
Borrower FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	No	Yes	Yes
State FE	No	No	Yes	No	No	Yes
Clustered SE	Borrower	Borrower	Borrower	Borrower	Borrower	Borrower
Observations	126,816	126,816	126,816	127,464	127,464	127,464
Adj. within R^2	0.065	0.016	0.016	0.14	0.032	0.032
Adjusted R^2	0.96	0.96	0.96	0.96	0.97	0.97

Table 3: P2P Lending and External Access to Credit – Sensitivity to Credit History

This table presents the results of OLS regressions of variables related to credit access from traditional financial intermediaries on receiving a P2P loan, its interaction with the *ex ante* length of credit history and borrower characteristics. The analysis is restricted to outcomes after the first application. The regression specification is as follows:

$$Y_{ist} = \lambda Credit\ history \times P2P\ loan_{is,t-1} + \beta P2P\ loan_{is,t-1} + \phi Credit\ history + \mathbf{X}_{ist}\zeta + \alpha_i + \gamma_s + \delta_t + u_{ist},$$

where Y_{ist} is a dependent variable and $\mathbf{X}_{ist}$ is a matrix of controls. The dependent variable *Revolver limits* is the total credit limit on revolving accounts. The dependent variable *Revolving accounts* is the number of open revolving accounts. The regressor of interest *P2P loan*$_{t-1}$ is the lagged indicator of an originated P2P loan. The economic magnitude of the coefficient of is measured relative to the mean level of the respective dependent variable on previous P2P loan application. *Credit history* is the length of the credit history, measured in years at the first application. *FICO* [†] is an indicator for a FICO score bin, where the † symbol denotes the range of the bin. *Log (income)* is the natural logarithm of monthly income, measured in thousands. *Log (employed)* is the natural logarithm of length of employment, measured in years. *Home owner* is an indicator of home ownership. *Debt-to-income* is the ratio of monthly debt to monthly income. All continuous variables are winsorized at the 1^{st} and the 99^{th} percentiles. The estimates of the intercept and fixed effects are omitted for brevity. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. T-statistics are presented in parentheses.

Dependent variable:	Revolver limits ($'000)			Revolving accounts		
	(1)	(2)	(3)	(1)	(2)	(3)
Credit history × P2P loan$_{t-1}$	-0.13***	-0.13***	-0.13***	-0.0046***	-0.0057***	-0.0057***
	(15.11)	(9.17)	(9.12)	(16.06)	(5.80)	(5.79)
P2P loan$_{t-1}$	5.58***	3.51***	3.49***	0.59***	0.22***	0.22***
	(-0.01)	(-0.44)	(-0.34)	(-0.14)	(-0.81)	(-0.75)
Credit history	-0.00034	-0.020	-0.015	-0.00065	-0.0037	-0.0034
	(0.78)	(0.69)	(0.74)	(3.13)	(2.07)	(2.05)
FICO [640-659]	2.04	1.78	1.93	0.67***	0.45**	0.45**
	(0.78)	(0.69)	(0.74)	(3.13)	(2.07)	(2.05)
FICO [660-679]	1.93	1.67	1.81	0.85***	0.63***	0.63***
	(0.73)	(0.63)	(0.69)	(3.97)	(2.89)	(2.87)
FICO [680-699]	2.60	2.26	2.41	0.93***	0.70***	0.70***
	(0.98)	(0.85)	(0.91)	(4.34)	(3.21)	(3.19)
FICO [700-719]	2.83	2.47	2.62	0.88***	0.65***	0.65***
	(1.07)	(0.93)	(0.99)	(4.09)	(2.96)	(2.94)
FICO [720-739]	2.96	2.60	2.77	0.80***	0.58***	0.58***
	(1.11)	(0.98)	(1.04)	(3.72)	(2.61)	(2.60)
FICO [740-759]	3.65	3.29	3.44	0.78***	0.55**	0.55**
	(1.36)	(1.23)	(1.28)	(3.58)	(2.47)	(2.46)
FICO [760-779]	3.12	2.63	2.81	0.70***	0.45**	0.45**
	(1.15)	(0.97)	(1.04)	(3.18)	(2.00)	(1.99)
FICO [780-799]	2.20	1.70	1.90	0.51**	0.26	0.26
	(0.80)	(0.62)	(0.69)	(2.30)	(1.15)	(1.14)
FICO [800-819]	-1.12	-1.72	-1.49	0.38	0.099	0.10
	(-0.40)	(-0.61)	(-0.53)	(1.63)	(0.42)	(0.44)
FICO [820-850]	-5.62*	-6.21**	-6.01*	0.089	-0.18	-0.18
	(-1.83)	(-2.03)	(-1.96)	(0.37)	(-0.74)	(-0.74)
Log (income)	3.95***	3.61***	3.60***	0.60***	0.53***	0.53***
	(11.13)	(10.47)	(10.59)	(14.10)	(13.49)	(13.50)
Log (employed)	0.24*	0.11	0.082	0.044***	0.020	0.019
	(1.92)	(0.86)	(0.67)	(3.38)	(1.58)	(1.50)
Home owner	1.78***	1.70***	1.68***	0.22***	0.20***	0.20***
	(2.89)	(2.76)	(2.73)	(4.34)	(4.00)	(3.96)
Debt-to-income	22.5***	20.2***	20.2***	3.25***	2.83***	2.84***
	(10.25)	(9.62)	(9.65)	(11.35)	(10.87)	(10.87)
Borrower FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	No	Yes	Yes
State FE	No	No	Yes	No	No	Yes
Clustered SE	Borrower	Borrower	Borrower	Borrower	Borrower	Borrower
Observations	126,816	126,816	126,816	127,464	127,464	127,464
Adj. within R^2	0.067	0.019	0.019	0.14	0.032	0.032
Adjusted R^2	0.96	0.96	0.96	0.96	0.97	0.97

Table 4: P2P Lending and External Access to Credit by FICO Score

This table presents the results of OLS regressions of variables related to credit access from traditional financial intermediaries on receiving a P2P loan and borrower characteristics for subsamples split by the *ex ante* FICO score bin of the borrower. The analysis is restricted to outcomes after the first application. The regression specification is as follows:

$$Y_{ist} = \beta P2P\ loan_{is,t-1} + \mathbf{X}_{ist}\zeta + \alpha_i + \gamma_s + \delta_t + u_{ist},$$

where Y_{ist} is a dependent variable and $\mathbf{X}_{ist}$ is a matrix of controls. The table reports coefficients on $P2P\ loan_{t-1}$ and their economic magnitudes relative to their mean level at the first application. The dependent variable *Revolver limits* is the total credit limit on revolving accounts. The dependent variable *Revolving accounts* is the number of open revolving accounts. The regressor of interest $P2P\ loan_{t-1}$ is the lagged indicator of an originated P2P loan. All regressions include borrower, state, and year fixed effects as well as controls. Controls include *FICO* bin indicators, *Log (income)*, *Log (employed)*, *Home owner*, and *Debt-to-income*. Standard errors are clustered at the borrower level. All continuous variables are winsorized at the 1^{st} and the 99^{th} percentiles. The estimates of the intercept, controls, and fixed effects are omitted for brevity. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable:	Revolver limits ($'000)		Revolving accounts		N
Sample split by FICO	Coefficient	Magnitude	Coefficient	Magnitude	
FICO [<640]	3.79	11.9%	0.81	15.5%	366
FICO [640–659]	1.30**	6.1%	0.18***	2.5%	15,064
FICO [660–679]	1.69***	6.5%	0.22***	2.7%	29,260
FICO [680–699]	1.66***	4.6%	0.16***	1.8%	28,492
FICO [700–719]	0.64	1.4%	-0.032	-0.4%	23,164
FICO [720–739]	0.43	0.8%	0.021	0.2%	15,394
FICO [740–759]	-1.29	-2.3%	-0.19**	-2.2%	7,808
FICO [760–779]	0.54	0.9%	0.069	0.8%	4,066
FICO [780–799]	-4.63**	-7.5%	-0.15	-1.9%	2,090
FICO [800–819]	2.98	4.6%	-0.10	-1.3%	1,204
FICO [820–850]	9.94**	25.3%	0.099	1.3%	550
Controls:	FICO bin indicators, Log (income), Log (employed), Home owner, and Debt-to-income				
Fixed effects:	Borrower, state, and year				
Standard errors:	Clustered at borrower level				

Table 5-A: P2P Lending and External Access to Credit: RDD – First Stage

This table reports the results of the first stage of the local fuzzy regression discontinuity design (RDD) regression with an indicator for crossing the funding threshold of 70% as an instrument for the lagged P2P loan origination. The regression specification is described by the following two equation system:

$$Y_{ist} = \beta P2P\ loan_{is,t-1} + f(Distance_{is,t-1}) + Above_{is,t-1} \times f(Distance_{is,t-1}) + \gamma_s + \delta_t + \epsilon_{ist} \qquad \text{(2nd stage)}$$

$$P2P\ loan_{is,t-1} = \phi Above_{is,t-1} + g(Distance_{is,t-1}) + Above_{is,t-1} \times g(Distance_{is,t-1}) + \gamma_s + \delta_t + \omega_{ist} \qquad \text{(1st stage)}$$

where Y_{ist} is a dependent variable, $Above_{is,t-1}$ is an instrument in the form of a binary variable equal to one if $Distance_{is,t-1} \geq 0$ and $-h \leq Distance_{is,t-1} \leq h$. The baseline bandwidth h is 10%. The dependent variable $P2P\ loan_{t-1}$ is the lagged indicator of an originated P2P loan. The instrument $Above_{t-1}$ is an indicator of the funding commitments being at least 70% of the requested loan amount. *Distance* is the difference between the forcing variable (percent funded) and the discontinuity threshold. *Distance sq.* is the squared distance from the discontinuity threshold. The estimates of the intercept and fixed effects are omitted for brevity. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. T-statistics are presented in parentheses.

Dependent variable:	P2P loan$_{t-1}$			
10% bandwidth	(1)	(2)	(3)	(4)
Above$_{t-1}$	0.36***	0.36***	0.36***	0.38***
	(8.36)	(9.34)	(9.62)	(7.97)
Distance	-0.19	-0.17	0.053	-0.75
	(-0.45)	(-0.44)	(0.20)	(-0.68)
Distance × Above$_{t-1}$			-0.40	-0.92
			(-0.55)	(-0.36)
Distance sq.		-1.48		-8.04
		(-0.39)		(-0.74)
Distance sq. × Above$_{t-1}$				22.6
				(0.84)
Cragg-Donald Wald F statistic	58.9	55.8	53.6	31.7
Kleibergen-Paap Wald F statistic	68.9	87.6	91.9	63.8
Borrower FE	No	No	No	No
Year FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Standard errors	Robust	Robust	Robust	Robust
Observations	821	821	821	821
Adjusted R^2	0.22	0.22	0.22	0.22

Table 5-B: P2P Lending and External Access to Credit: RDD – Second Stage

This table reports the results of the second stage of the local fuzzy regression discontinuity design (RDD) regression with an indicator for crossing the funding threshold of 70% as the (excluded) instrument for the lagged P2P loan origination. Table 5-A reports the first stage estimates. The regression specification is described by the following two equation system:

$$Y_{ist} = \beta P2P\ loan_{is,t-1} + f(Distance_{is,t-1}) + Above_{is,t-1} \times f(Distance_{is,t-1}) + \gamma_s + \delta_t + \epsilon_{ist} \qquad \text{(2nd stage)}$$
$$P2P\ loan_{is,t-1} = \phi Above_{is,t-1} + g(Distance_{is,t-1}) + Above_{is,t-1} \times g(Distance_{is,t-1}) + \gamma_s + \delta_t + \omega_{ist} \qquad \text{(1st stage)}$$

where Y_{ist} is a dependent variable, $Above_{is,t-1}$ is an instrument in the form of a binary variable equal to one if $Distance_{is,t-1} \geq 0$ and $-h \leq Distance_{is,t-1} \leq h$. The baseline bandwidth h is 10%. The dependent variable *Revolver limits* is the total credit limit on revolving accounts. The dependent variable *Revolving accounts* is the number of open revolving accounts. The regressor of interest $P2P\ loan_{t-1}$ is the lagged indicator of an originated P2P loan. The instrument $Above_{t-1}$ is an indicator of the funding commitments being at least 70% of the requested loan amount. *Distance* is the difference between the forcing variable (percent funded) and the discontinuity threshold. *Distance sq.* is the squared distance from the discontinuity threshold. The estimates of the intercept and fixed effects are omitted for brevity. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. T-statistics are presented in parentheses.

Dependent variable:	Revolver limits ($'000)				Revolving accounts			
10% bandwidth	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
P2P loan$_{i,t-1}$	57.2***	52.4***	51.0***	53.8**	2.34	2.53*	2.56*	2.82
	(3.18)	(2.96)	(2.87)	(2.31)	(1.58)	(1.70)	(1.71)	(1.49)
Economic magnitude	*118.1%*	*108.2%*	*105.3%*	*111.1%*	*31.0%*	*33.5%*	*33.9%*	*37.3%*
Distance	-150***	-139**	-53.5	-144	-2.97	-3.42	-6.51	-5.40
	(-2.72)	(-2.54)	(-0.64)	(-0.43)	(-0.60)	(-0.68)	(-0.80)	(-0.18)
Distance × Above$_{i,t-1}$			-162	-31.2			5.97	-3.93
			(-1.50)	(-0.07)			(0.55)	(-0.10)
Distance sq.		-824		-895		33.8		11.0
		(-1.61)		(-0.28)		(0.62)		(0.04)
Distance sq. × Above$_{i,t-1}$				459				86.6
				(0.12)				(0.24)
Borrower FE	No	No	No	No	No	No	No	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SE	Robust	Robust	Robust	Robust	Robust	Robust	Robust	Robust
Observations	812	812	812	812	821	821	821	821
Adjusted R^2	-0.16	-0.13	-0.12	-0.14	0.054	0.047	0.046	0.035

Table 6: P2P Lending and Credit Demand by Borrowers

This table presents the results of OLS regressions of variables related to credit demand by borrowers on receiving a P2P loan and borrower characteristics. The analysis is restricted to outcomes after the first application. The regression specification is as follows:

$$Y_{ist} = \beta P2P\ loan_{is,t-1} + \mathbf{X}_{ist}\zeta + \alpha_i + \gamma_s + \delta_t + u_{ist},$$

where Y_{ist} is a dependent variable and $\mathbf{X}_{ist}$ is a matrix of controls. The dependent variable *Revolving balance* is the total balance on revolving accounts. The dependent variable *Revolver utilization* is the ratio of balances to limits on revolving accounts. The dependent variable *Credit card utilization* is the ratio of balances to limits on bank card accounts. The regressor of interest *P2P loan*$_{t-1}$ is the lagged indicator of an originated P2P loan. The economic magnitude of the coefficient of is measured relative to the mean level of the respective dependent variable on previous P2P loan application. *FICO* [†] is an indicator for a FICO score bin, where the † symbol denotes the range of the bin. *Log (income)* is the natural logarithm of monthly income, measured in thousands. *Log (employed)* is the natural logarithm of length of employment, measured in years. *Home owner* is an indicator of home ownership. *Debt-to-income* is the ratio of monthly debt to monthly income. All continuous variables are winsorized at the 1^{st} and the 99^{th} percentiles. The estimates of the intercept and fixed effects are omitted for brevity. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. T-statistics are presented in parentheses.

Dependent variable:	Revolving balance ($'000)	Revolver utilization	Credit card utilization
P2P loan$_{t-1}$	-1.45***	-0.050***	-0.059***
	(-10.70)	(-21.95)	(-21.31)
Economic magnitude	*-7.7%*	*-10.3%*	*-10.8%*
FICO [640–659]	-0.79	0.012	0.024
	(-1.19)	(0.46)	(0.83)
FICO [660–679]	-1.73***	-0.057**	-0.055*
	(-2.58)	(-2.27)	(-1.93)
FICO [680–699]	-3.05***	-0.13***	-0.15***
	(-4.50)	(-5.27)	(-5.11)
FICO [700–719]	-5.08***	-0.20***	-0.22***
	(-7.37)	(-7.84)	(-7.80)
FICO [720–739]	-7.91***	-0.27***	-0.31***
	(-11.16)	(-10.76)	(-10.71)
FICO [740–759]	-11.2***	-0.35***	-0.41***
	(-15.22)	(-13.88)	(-14.01)
FICO [760–779]	-15.0***	-0.43***	-0.50***
	(-19.28)	(-16.66)	(-16.92)
FICO [780–799]	-18.5***	-0.49***	-0.57***
	(-22.28)	(-18.86)	(-19.24)
FICO [800–819]	-23.9***	-0.57***	-0.66***
	(-25.11)	(-21.62)	(-21.83)
FICO [820–850]	-28.7***	-0.63***	-0.73***
	(-21.47)	(-22.50)	(-22.98)
Log (income)	3.88***	0.049***	0.058***
	(13.66)	(12.31)	(13.44)
Log (employed)	0.10	0.00096	0.0016
	(1.28)	(0.69)	(0.98)
Home owner	2.45***	0.035***	0.037***
	(6.63)	(7.30)	(6.44)
Debt-to-income	22.0***	0.27***	0.33***
	(11.05)	(10.05)	(10.93)
Borrower FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes
Clustered SE	Borrower	Borrower	Borrower
Observations	127,464	127,464	127,464
Adj. within R^2	0.17	0.30	0.29
Adjusted R^2	0.97	0.89	0.87

Table 7: P2P Lending and Credit Demand by Borrowers by FICO Score

This table presents the results of OLS regressions of variables related to credit demand by borrowers on receiving a P2P loan and borrower characteristics for subsamples split by the ex ante FICO score bin of the borrower. The analysis is restricted to outcomes after the first application. The regression specification is as follows:

$$Y_{ist} = \beta P2P\ loan_{is,t-1} + \mathbf{X}_{ist}\zeta + \alpha_i + \gamma_s + \delta_t + u_{ist},$$

where Y_{ist} is a dependent variable and $\mathbf{X}_{ist}$ is a matrix of controls. The table reports coefficients on $P2P\ loan_{t-1}$ and their economic magnitudes relative to their mean level at the first application. The dependent variable *Revolving balance* is the total balance on revolving accounts. The dependent variable *Revolver utilization* is the ratio of balances to limits on revolving accounts. The dependent variable *Credit card utilization* is the ratio of balances to limits on bank card accounts. The regressor of interest $P2P\ loan_{t-1}$ is the lagged indicator of an originated P2P loan. All regressions include borrower, state, and year fixed effects as well as controls. Controls include *FICO* bin indicators, *Log (income)*, *Log (employed)*, *Home owner*, and *Debt-to-income*. Standard errors are clustered at the borrower level. All continuous variables are winsorized at the 1^{st} and the 99^{th} percentiles. The estimates of the intercept, controls, and fixed effects are omitted for brevity. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent variables:	Revolving balance ($'000)		Revolver utilization		Credit card utilization		N
Sample split by FICO	Coefficient	Magnitude	Coefficient	Magnitude	Coefficient	Magnitude	
FICO [<640]	-1.22	-8.1%	-0.061	-11.6%	0.0005	0.1%	366
FICO [640–659]	-1.88***	-15.6%	-0.12***	-20.3%	-0.14***	-20.7%	15,064
FICO [660–679]	-1.71***	-12.1%	-0.087***	-16.0%	-0.11***	-17.6%	29,260
FICO [680–699]	-1.84***	-9.6%	-0.076***	-14.7%	-0.095***	-16.3%	28,492
FICO [700–719]	-3.46***	-14.4%	-0.088***	-17.6%	-0.099***	-17.7%	23,164
FICO [720–739]	-4.57***	-17.8%	-0.093***	-20.4%	-0.11***	-21.8%	15,394
FICO [740–759]	-4.21***	-18.6%	-0.073***	-19.4%	-0.085***	-20.6%	7,808
FICO [760–779]	-2.20***	-14.4%	-0.026**	-9.1%	-0.013	-4.3%	4,066
FICO [780–799]	-3.53***	-23.1%	-0.031*	-14.8%	-0.043**	-20.0%	2,090
FICO [800–819]	-0.054	-0.4%	-0.0036	-2.5%	-0.02	-14.4%	1,204
FICO [820–850]	4.95**	38.7%	0.033	6.7%	0.025	25.6%	550
Controls:	FICO bin indicators, Log (income), Log (employed), Home owner, and Debt-to-income						
Fixed effects:	Borrower, state, and year						
Standard errors:	Clustered at borrower level						

Table 8: P2P Lending and Credit Demand by Borrowers: RDD – Second Stage

This table reports the results of the second stage of the local fuzzy regression discontinuity design (RDD) regression with an indicator for crossing the funding threshold of 70% as the (excluded) instrument for the lagged P2P loan origination. Table 5-A reports the first stage estimates. The regression specification is described by the following two equation system:

$$Y_{ist} = \beta P2P\ loan_{is,t-1} + f(Distance_{is,t-1}) + Above_{is,t-1} \times f(Distance_{is,t-1}) + \gamma_s + \delta_t + \epsilon_{ist} \quad \text{(2nd stage)}$$
$$P2P\ loan_{is,t-1} = \phi Above_{is,t-1} + g(Distance_{is,t-1}) + Above_{is,t-1} \times g(Distance_{is,t-1}) + \gamma_s + \delta_t + \omega_{ist} \quad \text{(1st stage)}$$

where Y_{ist} is a dependent variable, $Above_{is,t-1}$ is an instrument in the form of a binary variable equal to one if $Distance_{is,t-1} \geq 0$ and $-h \leq Distance_{is,t-1} \leq h$. The baseline bandwidth h is 10%. The dependent variable The dependent variable *Revolving balance* is the total balance on revolving accounts. The dependent variable *Revolver utilization* is the ratio of balances to limits on revolving accounts. The dependent variable *Credit card utilization* is the ratio of balances to limits on bank card accounts. The dependent variable *Delinquency* is an indicator of a delinquent borrower. The regressor of interest *P2P loan*$_{t-1}$ is the lagged indicator of an originated P2P loan. The instrument *Above*$_{t-1}$ is an indicator of the funding commitments being at least 70% of the requested loan amount. *Distance* is the difference between the forcing variable (percent funded) and the discontinuity threshold. *Distance sq.* is the squared distance from the discontinuity threshold. The estimates of the intercept and fixed effects are omitted for brevity. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. T-statistics are presented in parentheses.

Dependent variable:	Revolving balance ($'000)				Revolver utilization				Credit card utilization			
10% bandwidth	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
P2P loan$_{t-1}$	38.2***	35.1***	34.2***	29.3**	0.24**	0.24**	0.25**	0.29**	0.30***	0.31***	0.33***	0.35**
	(3.60)	(3.42)	(3.36)	(2.11)	(2.52)	(2.42)	(2.44)	(2.11)	(2.93)	(2.96)	(3.02)	(2.41)
Economic magnitude	*179.8%*	*165.2%*	*160.9%*	*137.9%*	*51.2%*	*51.2%*	*53.4%*	*61.9%*	*60.4%*	*62.5%*	*66.5%*	*70.5%*
Distance	-80.2**	-72.8**	-14.7	36.0	-0.34	-0.33	-0.42	-2.26	-0.51	-0.53	-0.90	-2.60
	(-2.58)	(-2.43)	(-0.35)	(0.18)	(-1.09)	(-1.05)	(-0.81)	(-1.08)	(-1.53)	(-1.58)	(-1.64)	(-1.17)
Distance × Above$_{t-1}$			-111*	-85.6			0.14	3.22			0.66	3.96
			(-1.83)	(-0.31)			(0.21)	(1.21)			(0.90)	(1.38)
Distance sq.		-562**		503		-0.45		-18.3		1.87		-16.9
		(-1.99)		(0.27)		(-0.13)		(-0.90)		(0.51)		(-0.79)
Distance sq. × Above$_{t-1}$				-1,354				4.74				-0.62
				(-0.60)				(0.20)				(-0.02)
Borrower FE	No	No	No	No	No	No	No	No	No	No	No	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SE	Robust	Robust	Robust	Robust	Robust	Robust	Robust	Robust	Robust	Robust	Robust	Robust
Observations	821	821	821	821	821	821	821	821	821	821	821	821
Adj. R^2	-0.19	-0.15	-0.14	-0.092	-0.04	-0.039	-0.044	-0.075	-0.004	-0.01	-0.019	-0.034

Table 9: P2P Lending, Total Debt, and Delinquencies

This table presents the results of OLS regressions of the total debt and the probability of delinquency on receiving a P2P loan and borrower characteristics. The analysis is restricted to outcomes after the first application. The regression specification is as follows:

$$Y_{ist} = \beta P2P\ loan_{is,t-1} + \mathbf{X}_{ist}\zeta + \alpha_i + \gamma_s + \delta_t + u_{ist},$$

where Y_{ist} is a dependent variable and $\mathbf{X}_{ist}$ is a matrix of controls. The dependent variable *Total debt* is the total balance on all credit accounts. The dependent variable *Delinquency* is an indicator of a delinquent borrower. The regressor of interest *P2P loan*$_{t-1}$ is the lagged indicator of an originated P2P loan. The economic magnitude of the coefficient of is measured relative to the mean level of the respective dependent variable on previous P2P loan application. *FICO* [†] is an indicator for a FICO score bin, where the † symbol denotes the range of the bin. *Log (income)* is the natural logarithm of monthly income, measured in thousands. *Log (employed)* is the natural logarithm of length of employment, measured in years. *Home owner* is an indicator of home ownership. *Debt-to-income* is the ratio of monthly debt to monthly income. All continuous variables are winsorized at the 1^{st} and the 99^{th} percentiles. The estimates of the intercept and fixed effects are omitted for brevity. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. T-statistics are presented in parentheses.

Dependent variable:	Total debt ($'000)			Delinquency (1/0)		
	(1)	(2)	(3)	(1)	(2)	(3)
P2P loan$_{t-1}$	10.8***	6.84***	6.84***	-0.011***	-0.0055*	-0.0054*
	(25.09)	(11.49)	(11.49)	(-5.01)	(-1.81)	(-1.77)
Economic magnitude	*7.1%*	*4.5%*	*4.5%*	*-6.7%*	*-3.4%*	*-3.3%*
FICO [640–659]	8.87	8.41	8.11	-0.080**	-0.080**	-0.080**
	(1.61)	(1.52)	(1.46)	(-2.16)	(-2.15)	(-2.15)
FICO [660–679]	6.36	5.86	5.52	-0.13***	-0.13***	-0.13***
	(1.16)	(1.07)	(1.00)	(-3.51)	(-3.49)	(-3.49)
FICO [680–699]	6.65	6.04	5.72	-0.17***	-0.17***	-0.17***
	(1.21)	(1.09)	(1.03)	(-4.70)	(-4.67)	(-4.67)
FICO [700–719]	3.65	3.01	2.74	-0.22***	-0.22***	-0.22***
	(0.66)	(0.54)	(0.49)	(-5.95)	(-5.92)	(-5.91)
FICO [720–739]	1.02	0.42	0.10	-0.24***	-0.24***	-0.24***
	(0.18)	(0.07)	(0.02)	(-6.51)	(-6.47)	(-6.46)
FICO [740–759]	-1.15	-1.76	-1.96	-0.26***	-0.26***	-0.26***
	(-0.20)	(-0.31)	(-0.34)	(-6.89)	(-6.86)	(-6.85)
FICO [760–779]	-4.68	-5.48	-5.67	-0.27***	-0.27***	-0.27***
	(-0.81)	(-0.95)	(-0.98)	(-7.03)	(-6.99)	(-6.98)
FICO [780–799]	-8.36	-9.23	-9.49	-0.27***	-0.27***	-0.27***
	(-1.42)	(-1.57)	(-1.60)	(-7.08)	(-7.03)	(-7.02)
FICO [800–819]	-17.5***	-18.4***	-18.8***	-0.27***	-0.27***	-0.27***
	(-2.82)	(-2.97)	(-3.01)	(-7.02)	(-6.97)	(-6.96)
FICO [820–850]	-24.3***	-25.3***	-25.5***	-0.26***	-0.26***	-0.26***
	(-3.67)	(-3.81)	(-3.83)	(-6.85)	(-6.80)	(-6.79)
Log (income)	0.96***	1.02***	1.01***	-0.013***	-0.012***	-0.012***
	(3.09)	(3.26)	(3.25)	(-3.48)	(-3.25)	(-3.27)
Log (employed)	1.01**	0.79*	0.74*	-0.0018	-0.0015	-0.0014
	(2.43)	(1.90)	(1.82)	(-0.91)	(-0.74)	(-0.70)
Home owner	204***	204***	204***	0.022***	0.022***	0.022***
	(61.58)	(61.62)	(61.57)	(2.80)	(2.82)	(2.83)
Debt-to-income				-0.067***	-0.061***	-0.061***
				(-3.06)	(-2.79)	(-2.76)
Borrower FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	No	Yes	Yes
State FE	No	No	Yes	No	No	Yes
Clustered SE	Borrower	Borrower	Borrower	Borrower	Borrower	Borrower
Observations	120,398	120,398	120,398	127,464	127,464	127,464
Adj. within R^2	0.52	0.51	0.51	0.047	0.038	0.038
Adjusted R^2	0.98	0.98	0.98	0.90	0.90	0.90

Table 10: P2P Lending, Total Debt, and Delinquencies: RDD – Second Stage

This table reports the results of the second stage of the local fuzzy regression discontinuity design (RDD) regression with an indicator for crossing the funding threshold of 70% as the (excluded) instrument for the lagged P2P loan origination. Table 5-A reports the first stage estimates. The regression specification is described by the following two equation system:

$$Y_{ist} = \beta P2P\ loan_{is,t-1} + f(Distance_{is,t-1}) + Above_{is,t-1} \times f(Distance_{is,t-1}) + \gamma_s + \delta_t + \epsilon_{ist} \quad \text{(2nd stage)}$$

$$P2P\ loan_{is,t-1} = \phi Above_{is,t-1} + g(Distance_{is,t-1}) + Above_{is,t-1} \times g(Distance_{is,t-1}) + \gamma_s + \delta_t + \omega_{ist} \quad \text{(1st stage)}$$

where Y_{ist} is a dependent variable, $Above_{is,t-1}$ is an instrument in the form of a binary variable equal to one if $Distance_{is,t-1} \geq 0$ and $-h \leq Distance_{is,t-1} \leq h$. The baseline bandwidth h is 10%. The dependent variable *Total debt* is the total balance on all credit accounts. The dependent variable *Delinquency* is an indicator of a delinquent borrower. The regressor of interest $P2P\ loan_{t-1}$ is the lagged indicator of an originated P2P loan. The instrument $Above_{t-1}$ is an indicator of the funding commitments being at least 70% of the requested loan amount. *Distance* is the difference between the forcing variable (percent funded) and the discontinuity threshold. *Distance sq.* is the squared distance from the discontinuity threshold. The estimates of the intercept and fixed effects are omitted for brevity. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. T-statistics are presented in parentheses.

Dependent variable:	Total debt ($'000)				Delinquency (1/0)			
10% bandwidth	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
P2P $\text{loan}_{i,t-1}$	216***	193***	182***	149*	0.0085	-0.032	-0.044	0.094
	(3.16)	(2.85)	(2.68)	(1.67)	(0.06)	(-0.22)	(-0.29)	(0.51)
Economic magnitude	*119.3%*	*106.6%*	*100.5%*	*82.3%*	*5.0%*	*-18.7%*	*-25.7%*	*55.0%*
Distance	-422*	-362	119	1,160	0.00066	0.097	0.85	-1.76
	(-1.84)	(-1.59)	(0.34)	(0.85)	(0.00)	(0.22)	(1.17)	(-0.66)
Distance × $\text{Above}_{i,t-1}$			-899***	-2,307			-1.44	0.64
			(-1.93)	(-1.23)			(-1.52)	(0.18)
Distance sq.		-3,909*		10,422		-7.27		-25.9
		(-1.68)		(0.75)		(-1.56)		(-1.03)
Distance sq. × $\text{Above}_{i,t-1}$				-6,526				32.4
				(-0.39)				(1.05)
Borrower FE	No	No	No	No	No	No	No	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SE	Robust	Robust	Robust	Robust	Robust	Robust	Robust	Robust
Observations	786	786	786	786	821	821	821	821
Adjusted R^2	-0.024	-0.00049	0.0096	0.029	-0.0067	-0.0073	-0.0086	-0.011

Table 11: Propensity to Borrow Repeatedly from P2P Lending Platforms

This table presents the results of estimating the propensity to become a repeat borrower based on P2P loan and borrower characteristics. I use the linear probability (OLS) and logit regressions. The regression specifications are as follows:

$$\textit{Repeat borrower}_i = \alpha + \mathbf{X}_i\beta + \epsilon_i \qquad \text{(linear)}$$

$$\textit{Repeat borrower}_i = \frac{1}{1+e^{-(\alpha+\mathbf{X}_i\beta+\epsilon_i)}}, \qquad \text{(logit)}$$

where $\mathbf{X}_i$ is a matrix of regressors. The dependent variable *Repeat borrower* is an indicator of the borrower who submitted P2P loan applications on the platform several times. *Interest rate (APR)* is the interest rate on the loan plus fees. *FICO* [†] is an indicator for a FICO score bin, where the † symbol denotes the range of the bin. *Log (income)* is the natural logarithm of monthly income, measured in thousands. *Log (employed)* is the natural logarithm of length of employment, measured in years. *Home owner* is an indicator of home ownership. *Debt-to-income* is the ratio of monthly debt to monthly income. *P2P loan* is the indicator of an originated P2P loan. All continuous variables are winsorized at the 1^{st} and the 99^{th} percentiles. The estimate of the intercept is omitted for brevity. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. T-statistics are presented in parentheses.

Dependent variable:	Repeat borrower (1/0)							
	linear probability				logit			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Intercept	0.13***	0.047***	0.28***	0.13***	-1.88***	-2.61***	-1.04***	-2.33***
	(74.11)	(7.98)	(137.62)	(21.37)	(-162.99)	(-39.34)	(-79.56)	(-33.89)
Interest rate (APR)	0.30***		0.24***		1.99***		1.70***	
	(33.65)		(26.81)		(34.52)		(27.29)	
P2P loan			-0.23***	-0.26***			-1.48***	-1.80***
			(-174.26)	(-184.64)			(-179.67)	(-193.84)
FICO [<640]		0.21***		0.28***		1.45***		2.11***
		(10.89)		(14.73)		(13.32)		(16.73)
FICO [640–659]		0.077***		0.16***		0.71***		1.32***
		(13.56)		(27.25)		(10.87)		(19.58)
FICO [660–679]		0.086***		0.17***		0.78***		1.36***
		(15.47)		(28.60)		(12.04)		(20.38)
FICO [680–699]		0.085***		0.16***		0.77***		1.30***
		(15.14)		(27.36)		(11.87)		(19.51)
FICO [700–719]		0.082***		0.16***		0.75***		1.27***
		(14.53)		(26.60)		(11.52)		(19.01)
FICO [720–739]		0.078***		0.15***		0.72***		1.25***
		(13.75)		(25.76)		(11.07)		(18.50)
FICO [740–759]		0.070***		0.14***		0.66***		1.13***
		(11.88)		(22.64)		(9.91)		(16.42)
FICO [760–779]		0.060***		0.12***		0.58***		1.00***
		(9.70)		(19.20)		(8.48)		(14.12)
FICO [780–799]		0.041***		0.093***		0.42***		0.75***
		(6.26)		(13.75)		(5.82)		(10.04)
FICO [800–819]		0.033***		0.064***		0.35***		0.54***
		(4.61)		(8.52)		(4.50)		(6.64)
Log (income)		0.042***		0.036***		0.30***		0.28***
		(34.75)		(31.55)		(34.56)		(30.71)
Log (employed)		-0.0060***		-0.0034***		-0.043***		-0.024***
		(-12.24)		(-7.38)		(-12.13)		(-6.59)
Home owner		-0.0030**		0.0092***		-0.018**		0.080***
		(-2.40)		(7.78)		(-1.96)		(8.17)
Debt-to-income		-0.12***		-0.061***		-1.06***		-0.58***
		(-21.20)		(-11.19)		(-21.88)		(-11.68)
Borrower FE	No	No	No	No	No	No	No	No
Year FE	No	No	No	No	No	No	No	No
State FE	No	No	No	No	No	No	No	No
SE	Robust	Robust	Robust	Robust	Robust	Robust	Robust	Robust
Observations	445,334	392,114	445,334	392,114	445,334	392,114	445,334	392,114
Adj./Pseudo R^2	0.003	0.007	0.083	0.12	0.003	0.008	0.084	0.12

Appendix A: Definitions of Variables

Borrower risk profile

Credit history (years) is the length of the credit history, measured in years; it is derived as the difference between the loan application date and the date when the oldest account on the borrower's credit record was opened.

Debt-to-income is the ratio of the monthly debt reported by the credit bureau to monthly income reported by a borrower on the loan application, measured in decimals.

Employment (years) is the length of employment with the current employer self-reported by the borrower, measured in years; it includes both formal employment and self-employment.

FICO [†] is an indicator of a bin of the FICO classic score reported by the credit bureau, where the † symbol denotes the range of the bin.

FICO score is the midpoint value of the binned FICO classic score reported by the credit bureau.

Home owner (1/0) is an indicator of home ownership that equals to one if the borrower has an outstanding mortgage on her credit report or has provided documentation supporting home ownership and zero otherwise.

Log (employed) is the natural logarithm of the number of years the borrower is employed with the current employer.

Log (income) is the natural logarithm of the monthly income reported by a borrower on the loan application.

Monthly income ($'000) is the dollar amount of monthly income reported by a borrower on the loan application, measured in thousands.

Consumer credit variables

Current accounts is the total number of open or closed accounts in the borrower's name over the past 6 months reported by the credit bureau; it includes both accounts that the borrower is paying on time and the ones that are currently late, including charge-offs.

Credit card utilization is the ratio of all balances owed on open bank cards to credit limits on bank card accounts.

Delinquency (1/0) is an indicator of a delinquent borrower; delinquencies include any past due amounts owed by the borrower, such as accounts in Chapter 13 bankruptcies, charge-offs, or other unpaid derogatory account balances reported to the credit bureau.

Installment balance ($'000) is the total balance on installment trades outstanding reported by the credit bureau, measured in thousands.

Mortgage balance ($'000) is the balance on real estate trades reported by the credit bureau, measured in thousands.

Open accounts is the total number of current accounts that are still open reported by the credit bureau.

Revolver limits ($'000) is the total credit limit on revolving accounts, measured in thousands; it is calculated from the credit bureau data as the revolving balance divided by one minus percentage of revolving credit available.

Revolver utilization is the ratio of the balances owed on all revolving accounts to credit limits on these accounts; it is calculated from the credit bureau data as 1 minus percentage of revolving credit available.

Revolving accounts is the total number of open revolving accounts reported by the credit bureau.

Revolving balance ($'000) is the total outstanding balance that the borrower owes on open credit cards or other revolving credit accounts reported by the credit bureau, measured in thousands.

Total debt ($'000) is the total balance on all credit accounts, measured in thousands; it is calculated as the sum of revolving, installment, and mortgage balances reported by the credit bureau.

Peer-to-peer loan application

Above (1/0) is an indicator of the funding commitments being at least 70% of the requested loan amount; it is equal to 1 if the percent of the requested loan amount funded by investors is at least 70% and 0 otherwise.

Distance is the difference between the percent funded and the funding threshold.

Distance sq. is the squared distance from the funding threshold.

Interest rate (APR) is the average annual percentage rate (APR) on the loan set by Prosper, stated as a percent; it includes the borrower rate and any applicable fees, such as the origination fee.

Listing amount is the P2P loan amount requested by borrower.

P2P loan (1/0) is an indicator of an originated P2P loan; it is equal to 1 if the loan was originated and 0 otherwise.

P2P loan (placebo) (1/0) is an indicator of the placebo P2P loan origination; it is equal to 1 if the loan application was above the threshold and expired unfunded and 0 if the loan application was cancelled or withdrawn.

Percent funded is the percent of the requested P2P loan amount funded by investors, stated either as percent or as a fraction.

Repeat borrower (1/0) is an indicator of a repeat P2P loan applicant; it is equal to 1 if a borrower has more than 1 application on Prosper, including any applications that were cancelled, withdrawn or that expired unfunded, and 0 otherwise.

Appendix B: Supplementary Figures and Tables

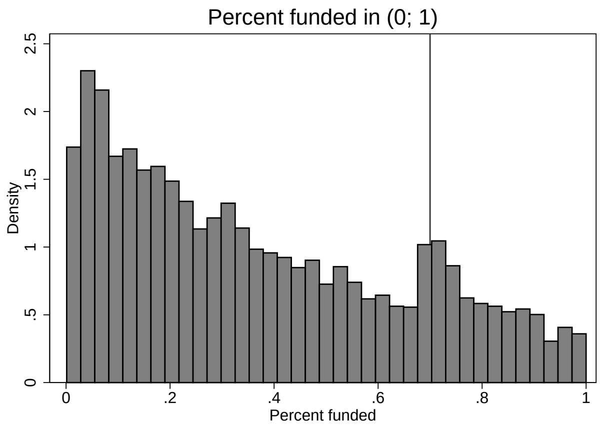

Figure B.1: Density of Forcing Variable

This graph shows the density of forcing variable *Percent funded* for all loan applications and applications within the 10% bandwidth around the discontinuity threshold of 70%. I trim the density to remove applications that are completely unfunded and that are fully-funded for the ease of exposition as there are significant spikes in the density at both ends. *Percent funded* is the percent of the listing funded by Prosper investors. The vertical line represents the funding threshold.

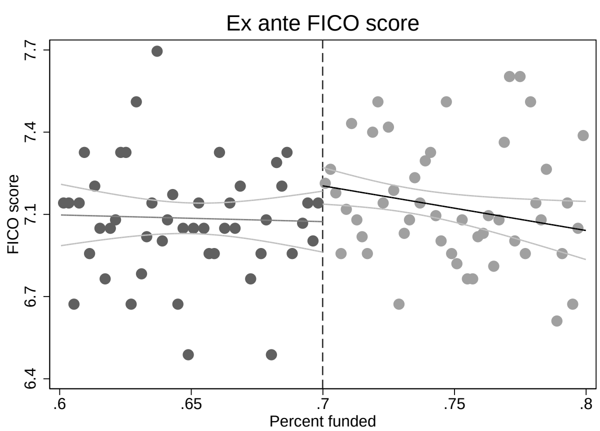

Figure B.2: Ex Ante and Ex Post FICO Score

This graph illustrates that the FICO score does not jump around the threshold. It shows ex ante (lagged) and ex post (after treatment) FICO score as a function of the forcing variable. Statistical tests reject the jump at conventional levels of significance. The baseline bandwidth is 10%. The binned averages represent the conditional expectation of the FICO score. *Percent funded* is the percent of the listing funded by Prosper investors. *FICO score* is the midpoint value of the binned FICO classic score reported by the credit bureau. All outcome variables are winsorized at the 1^{st} and the 99^{th} percentiles. The straight lines are fitted values. The light gray lines are 99% confidence intervals.

Table B.1: Friends and Family Investments into P2P Loans

This table describes investments from friends and family into P2P loans for the sub-period starting from January 2011 after Prosper switched to pre-set interest rates up to April 2013 when the whole loan program was introduced and Prosper stopped disclosing this information. The data is manually collected from Prosper's sales reports. *% funded* is the percent of the listing funded by Prosper investors. *Adjusted % funded* is calculated as the amount of the loan funded minus friends and family investments divided by the requested loan amount.

	% funded = 100%	% funded ∈ (80%; 100%)	% funded ∈ [70%; 80%]
Observations in subsample	34,564	424	415
Observations with friends and family investments	229	6	7
% of observations with friends and family investments	0.007	0.014	0.017
Average investment by friends and family	551	638	593
Average % percent funded by friends and family	0.082	0.073	0.030
Observations with adjusted % funded falling into:			
Adjusted % funded ∈ (80%; 100%)	205	5	N/A
Adjusted % funded ∈ [70%; 80%]	9	0	4
Adjusted % funded ∈ [60%; 70%)	3	0	3
Adjusted % funded ∈ (40%; 60%)	5	1	0
Adjusted % funded ∈ [0%; 40%]	7	0	0

Table B.2: P2P Lending, Total Debt, and External Access to Credit – Robustness

This table presents the results of OLS regressions of the total debt and variables related to credit access from traditional financial intermediaries on receiving a P2P loan and borrower characteristics based on alternative sample restrictions and definitions of the regressor of interest. Panel A reports the baseline regression. Panel B excludes cancelled applications from the analysis. Panel C excludes applications with 31 or fewer days between them to remove stale credit reports. Panel D uses all subsequent loan applications and an alternative P2P loan variable which is the number of prior P2P loans of the borrower. Panel E uses the baseline P2P loan indicator but uses all subsequent loan applications. The regression specification is as follows:

$$Y_{ist} = \beta P2P\ loan_{is,t-1} + \mathbf{X}_{ist}\zeta + \alpha_i + \gamma_s + \delta_t + u_{ist},$$

The table reports coefficients on *P2P loan*$_{t-1}$ and their economic magnitudes relative to their mean level at the first application. The dependent variable *Total debt* is the total balance on all credit accounts. The dependent variable *Revolver limits* is the total credit limit on revolving accounts. The dependent variable *Revolving accounts* is the number of open revolving accounts. The regressor of interest *P2P loan*$_{t-1}$ is the lagged indicator of an originated P2P loan. All regressions include borrower, state, and year fixed effects as well as controls. Controls include *FICO* bin indicators, *Log (income)*, *Log (employed)*, *Home owner*, and *Debt-to-income*. Standard errors are clustered at the borrower level. All continuous variables are winsorized at the 1^{st} and the 99^{th} percentiles. The estimates of the intercept, controls, and fixed effects are omitted for brevity. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable:	Total debt ($'000)			Revolver limits ($'000)			Revolving accounts		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Panel A: Baseline regression									
P2P loan$_{t-1}$	10.8***	6.84***	6.84***	3.14***	1.00***	0.99***	0.50***	0.11***	0.11***
Economic magnitude	*7.1%*	*4.5%*	*4.5%*	*8.0%*	*2.6%*	*2.5%*	*6.1%*	*1.3%*	*1.3%*
Panel B: Cancelled applications excluded									
P2P loan$_{t-1}$	10.3***	6.19***	6.17***	2.71***	1.03***	1.01***	0.44***	0.092***	0.092***
Economic magnitude	*6.8%*	*4.1%*	*4.1%*	*6.9%*	*2.6%*	*2.6%*	*5.3%*	*1.1%*	*1.1%*
Panel C: Stale credit reports excluded									
P2P loan$_{t-1}$	10.6***	6.49***	6.49***	2.72***	0.56**	0.54**	0.44***	0.042*	0.041
Economic magnitude	*7.0%*	*4.3%*	*4.3%*	*7.0%*	*1.4%*	*1.4%*	*5.3%*	*0.5%*	*0.5%*
Panel D: All subsequent applications - cumulative effect									
P2P loan$_{t-1}$	9.60***	5.53***	5.58***	3.02***	0.87***	0.88***	0.49***	0.098***	0.099***
Economic magnitude	*6.3%*	*3.7%*	*3.7%*	*7.7%*	*2.2%*	*2.3%*	*5.9%*	*1.2%*	*1.2%*
Panel E: All subsequent applications - marginal effect									
P2P loan$_{t-1}$	9.43***	4.49***	4.46***	2.53***	0.37**	0.37**	0.41***	0.061***	0.062***
Economic magnitude	*6.2%*	*3.0%*	*2.9%*	*6.5%*	*0.9%*	*0.9%*	*5.0%*	*0.7%*	*0.8%*
Controls:	FICO bin indicators, Log (income), Log (employed), Home owner, and Debt-to-income								
Fixed effects:	Borrower, state, and year								
Standard errors:	Clustered at borrower level								

Table B.3: P2P Lending, Total Debt, and External Access to Credit by Time between Applications

This table presents the results of OLS regressions of the total debt and variables related to credit access from traditional financial intermediaries on receiving a P2P loan and borrower characteristics by time between applications. The analysis is restricted to outcomes after the first application. The regression specification is:

$$Y_{ist} = \beta P2P\ loan_{is,t-1} + \mathbf{X}_{ist}\zeta + \alpha_i + \gamma_s + \delta_t + u_{ist},$$

where Y_{ist} is a dependent variable and $\mathbf{X}_{ist}$ is a matrix of controls. The dependent variable *Total debt* is the total balance on all credit accounts. The dependent variable *Revolver limits* is the total credit limit on revolving accounts. The dependent variable *Revolving accounts* is the number of open revolving accounts. The regressor of interest *P2P loan*$_{t-1}$ is the lagged indicator of an originated P2P loan. The economic magnitude of the coefficient of is measured relative to the mean level of the respective dependent variable on previous P2P loan application. *FICO* [†] is an indicator for a FICO score bin, where the † symbol denotes the range of the bin. *Log (income)* is the natural logarithm of monthly income, measured in thousands. *Log (employed)* is the natural logarithm of length of employment, measured in years. *Home owner* is an indicator of home ownership. *Debt-to-income* is the ratio of monthly debt to monthly income. All continuous variables are winsorized at the 1st and the 99th percentiles. The estimates of the intercept and fixed effects are omitted for brevity. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. T-statistics are presented in parentheses.

Dependent variable:	Total debt ($'000)			Revolver limits ($'000)			Revolving accounts		
Time (years):	(≤1]	(1–2]	(>2)	(≤1]	(1–2]	(>2)	(≤1]	(1–2]	(>2)
P2P loan$_{t-1}$	6.60***	9.45***	-6.66	1.66***	-0.49	-1.79	0.16***	0.023	-0.50
	(10.55)	(5.86)	(-0.79)	(7.31)	(-0.94)	(-0.48)	(7.32)	(0.37)	(-1.14)
Economic magnitude	*4.4%*	*6.2%*	*-4.4%*	*4.2%*	*-1.3%*	*-4.6%*	*1.9%*	*0.3%*	*-6.1%*
FICO [640–659]	6.02	-0.16	39.5*	-1.27	2.57	11.5	0.59	0.15	0.96
	(0.56)	(-0.03)	(1.75)	(-1.33)	(0.71)	(0.97)	(1.53)	(0.49)	(1.61)
FICO [660–679]	3.60	-2.47	21.8	-1.01	1.58	10.3	0.77**	0.31	1.49**
	(0.33)	(-0.46)	(1.10)	(-1.05)	(0.43)	(0.81)	(2.00)	(1.02)	(2.45)
FICO [680–699]	3.54	-2.05	26.4	-0.24	1.57	13.7	0.86**	0.32	1.81***
	(0.32)	(-0.37)	(1.30)	(-0.25)	(0.43)	(0.99)	(2.22)	(1.05)	(3.00)
FICO [700–719]	-0.084	-4.40	44.9**	-0.17	2.19	15.3	0.79**	0.31	1.55***
	(-0.01)	(-0.79)	(2.13)	(-0.17)	(0.59)	(1.14)	(2.04)	(1.02)	(2.59)
FICO [720–739]	-2.61	-7.12	25.9	0.079	1.95	13.7	0.73*	0.24	1.17*
	(-0.24)	(-1.23)	(1.20)	(0.08)	(0.53)	(1.02)	(1.87)	(0.77)	(1.75)
FICO [740–759]	-5.25	-7.74	25.7	0.00052	4.45	16.6	0.67*	0.27	1.46**
	(-0.48)	(-1.24)	(1.07)	(0.00)	(1.18)	(1.23)	(1.73)	(0.84)	(2.14)
FICO [760–779]	-9.14	-11.1*	26.5	-0.49	3.09	20.0	0.55	0.18	1.91**
	(-0.82)	(-1.69)	(1.14)	(-0.42)	(0.79)	(1.46)	(1.42)	(0.55)	(2.54)
FICO [780–799]	-11.9	-16.8**	16.3	-1.72	2.70	23.1	0.42	-0.13	1.78*
	(-1.06)	(-2.44)	(0.68)	(-1.37)	(0.67)	(1.62)	(1.08)	(-0.38)	(1.86)
FICO [800–819]	-18.7*	-30.6***	-5.50	-3.85***	-2.68	3.78	0.30	-0.26	0.47
	(-1.65)	(-3.67)	(-0.22)	(-2.64)	(-0.65)	(0.25)	(0.76)	(-0.70)	(0.56)
FICO [820–850]	-26.7**	-34.3***	11.9	-9.13***	-5.87	10.7	0.061	-0.55	-0.51
	(-2.26)	(-4.12)	(0.45)	(-4.62)	(-1.16)	(0.73)	(0.15)	(-1.33)	(-0.49)
Log (income)	0.64***	8.55**	-18.3	2.39***	10.3***	11.2**	0.38***	1.36***	1.48*
	(3.15)	(2.09)	(-0.97)	(6.82)	(6.87)	(2.30)	(9.62)	(8.15)	(1.85)
Log (employed)	0.36	1.34	-2.28	0.14	-0.016	-1.14	0.030**	0.0042	-0.20
	(0.94)	(1.29)	(-0.58)	(1.30)	(-0.05)	(-0.86)	(2.56)	(0.13)	(-1.31)
Home owner	207***	201***	189***	1.96**	1.73*	-1.19	0.22***	0.23***	-0.31
	(45.33)	(40.02)	(11.07)	(2.44)	(1.68)	(-0.57)	(3.77)	(2.66)	(-0.73)
Debt-to-income				14.2***	35.5***	22.2**	2.17***	4.48***	2.83
				(6.68)	(8.05)	(2.19)	(8.28)	(9.92)	(1.58)
Borrower FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Borrower	Borrower	Borrower	Borrower	Borrower	Borrower	Borrower	Borrower	Borrower
Observations	103,674	14,826	732	108,920	15,872	840	109,476	15,944	850
Adj. within R^2	0.52	0.50	0.55	0.015	0.024	0.0065	0.031	0.040	0.041
Adjusted R^2	0.99	0.94	0.92	0.98	0.89	0.74	0.74	0.98	0.90

Table B.4-A: P2P Lending, Total Debt, and External Access to Credit: Placebo RDD – First Stage

This table reports the results of the first stage of the placebo local fuzzy regression discontinuity design (RDD) regression with an indicator for crossing the placebo funding threshold of 70% as an instrument for the lagged placebo P2P loan origination. The placebo RDD is estimated based on a subsample of borrowers not subject to the 70% funding threshold. The regression specification is described by the following two equation system:

$$Y_{ist} = \beta P2P\ loan_{is,t-1}(placebo) + f(Distance_{is,t-1}) + Above_{is,t-1} \times f(Distance_{is,t-1}) + \gamma_s + \delta_t + \epsilon_{ist} \qquad \text{(2nd stage)}$$

$$P2P\ loan_{is,t-1}(placebo) = \phi Above_{is,t-1} + g(Distance_{is,t-1}) + Above_{is,t-1} \times g(Distance_{is,t-1}) + \gamma_s + \delta_t + \omega_{ist} \qquad \text{(1st stage)}$$

where Y_{ist} is a dependent variable, $Above_{is,t-1}$ is an instrument in the form of a binary variable equal to one if $Distance_{is,t-1} \geq 0$ and $-h \leq Distance_{is,t-1} \leq h$. The baseline bandwidth h is 10%. The dependent variable $P2P\ loan_{t-1}(placebo)$ is the lagged indicator of the placebo P2P loan origination which equals to 1 if the loan application was above the threshold and expired and 0 if the loan application was cancelled or withdrawn. The instrument $Above_{t-1}$ is an indicator of the funding commitments being at least 70% of the requested loan amount. *Distance* is the difference between the forcing variable (percent funded) and the discontinuity threshold. *Distance sq.* is the squared distance from the discontinuity threshold. The estimates of the intercept and fixed effects are omitted for brevity. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. T-statistics are presented in parentheses.

Dependent variable:	P2P $\text{loan}_{t-1}(placebo)$			
10% bandwidth	(1)	(2)	(3)	(4)
Above_{t-1}	0.91***	0.92***	0.92***	0.87***
	(45.18)	(38.69)	(38.67)	(25.50)
Distance	-0.40**	-0.48**	-0.15**	0.064
	(-2.20)	(-2.10)	(-2.30)	(0.29)
Distance × Above_{t-1}			-0.63	1.58
			(-1.41)	(0.97)
Distance sq.		-3.52		2.04
		(-1.59)		(0.95)
Distance sq. × Above_{t-1}				-26.5
				(-1.59)
Cragg-Donald Wald F statistic	1,658	1,657	1,652	668
Kleibergen-Paap Wald F statistic	1,701	1,286	1,285	529
Borrower FE	No	No	No	No
Year FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Standard errors	Robust	Robust	Robust	Robust
Observations	1,855	1,855	1,855	1,855
Adjusted R^2	0.80	0.80	0.80	0.80

Table B.4-B: P2P Lending, Total Debt, and External Access to Credit: Placebo RDD – Second Stage

This table reports the results of the second stage of the placebo local fuzzy regression discontinuity design (RDD) regression with an indicator for crossing the placebo funding threshold of 70% as the (excluded) instrument for the lagged placebo P2P loan origination. The placebo RDD is estimated based on a subsample of borrowers not subject to the 70% funding threshold. Table B.4-A reports the first stage estimates. The regression specification is described by the following two equation system:

$$Y_{ist} = \beta P2P\ loan_{is,t-1}(placebo) + f(Distance_{is,t-1}) + Above_{is,t-1} \times f(Distance_{is,t-1}) + \gamma_s + \delta_t + \epsilon_{ist} \quad \text{(2nd stage)}$$

$$P2P\ loan_{is,t-1}(placebo) = \phi Above_{is,t-1} + g(Distance_{is,t-1}) + Above_{is,t-1} \times g(Distance_{is,t-1}) + \gamma_s + \delta_t + \omega_{ist} \quad \text{(1st stage)}$$

where Y_{ist} is a dependent variable, $Above_{is,t-1}$ is an instrument in the form of a binary variable equal to one if $Distance_{is,t-1} \geq 0$ and $-h \leq Distance_{is,t-1} \leq h$. The baseline bandwidth h is 10%. The dependent variable *Total debt* is the total balance on all credit accounts. The dependent variable *Revolver limits* is the total credit limit on revolving accounts. The dependent variable *Revolving accounts* is the number of open revolving accounts. The regressor of interest $P2P\ loan_{t-1}(placebo)$ is the lagged indicator of the placebo P2P loan origination which equals to 1 if the loan application was above the threshold and expired and 0 if the loan application was cancelled or withdrawn. The instrument $Above_{t-1}$ is an indicator of the funding commitments being at least 70% of the requested loan amount. *Distance* is the difference between the forcing variable (percent funded) and the discontinuity threshold. *Distance sq.* is the squared distance from the discontinuity threshold. The estimates of the intercept and fixed effects are omitted for brevity. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. T-statistics are presented in parentheses.

Dependent variable:	Total debt ($'000)				Revolver limits ($'000)				Revolving accounts			
10% bandwidth	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
P2P loan$_{i,t-1}$(*placebo*)	9.42	7.59	7.01	-16.0	0.64	1.18	1.23	-6.14	-0.61	-0.63	-0.62	-0.41
	(0.42)	(0.34)	(0.31)	(-0.47)	(0.11)	(0.20)	(0.21)	(-0.68)	(-1.17)	(-1.19)	(-1.17)	(-0.49)
Distance	-49.3	-30.7	-151	-43.0	34.5	29.2	58.5	232	6.37	6.56*	6.27	14.0
	(-0.30)	(-0.18)	(-0.70)	(-0.05)	(0.86)	(0.71)	(1.11)	(1.04)	(1.63)	(1.65)	(1.18)	(0.64)
Distance × Above$_{i,t-1}$			252	1,293			-59.1	-9.14			0.24	-26.4
			(0.71)	(0.96)			(-0.67)	(-0.03)			(0.03)	(-0.78)
Distance sq.		912		1,098		-262		1,717		9.30		75.8
		(0.54)		(0.14)		(-0.64)		(0.84)		(0.23)		(0.37)
Distance sq. × Above$_{i,t-1}$				-12,964				-4,044				117
				(-0.94)				(-1.15)				(0.35)
Borrower FE	No	No	No	No	No	No	No	No	No	No	No	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SE	Robust	Robust	Robust	Robust	Robust	Robust	Robust	Robust	Robust	Robust	Robust	Robust
Observations	1,567	1,567	1,567	1,567	1,587	1,587	1,587	1,587	1,645	1,645	1,645	1,645
Adjusted R^2	0.021	0.021	0.021	0.019	0.027	0.026	0.026	0.026	0.031	0.031	0.031	0.031

Table B.5: P2P Lending, Total Debt, and External Access to Credit: RDD – Robustness to Bandwidth (IV Stage)

This table reports the results of the second stage of the local fuzzy regression discontinuity design (RDD) regression with an indicator for crossing the funding threshold of 70% as an instrument for the lagged P2P loan origination for various bandwidths. The regression specification is described by the following two equation system:

$$Y_{ist} = \beta P2P\ loan_{is,t-1} + f(Distance_{is,t-1}) + Above_{is,t-1} \times f(Distance_{is,t-1}) + \gamma_s + \delta_t + \epsilon_{ist} \quad \text{(2nd stage)}$$

$$P2P\ loan_{is,t-1} = \phi Above_{is,t-1} + g(Distance_{is,t-1}) + Above_{is,t-1} \times g(Distance_{is,t-1}) + \gamma_s + \delta_t + \omega_{ist} \quad \text{(1st stage)}$$

where Y_{ist} is a dependent variable, $Above_{is,t-1}$ is an instrument in the form of a binary variable equal to one if $Distance_{is,t-1} \geq 0$ and $-h \leq Distance_{is,t-1} \leq h$. The baseline bandwidth h is 10%. The dependent variable *Total debt* is the total balance on all credit accounts. The dependent variable *Revolver limits* is the total credit limit on revolving accounts. The dependent variable *Revolving accounts* is the number of open revolving accounts. The regressor of interest *P2P loan*$_{t-1}$ is the lagged indicator of an originated P2P loan. The instrument *Above*$_{t-1}$ is an indicator of the funding commitments being at least 70% of the requested loan amount. *Distance* is the difference between the forcing variable (percent funded) and the discontinuity threshold. *Distance sq.* is the squared distance from the discontinuity threshold. The estimates of the intercept and fixed effects are omitted for brevity. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. T-statistics are presented in parentheses.

Dependent variable:	Total debt ($'000)				Revolver limits ($'000)				Revolving accounts			
Bandwidth:	[5%]	[10%]	[15%]	[20%]	[5%]	[10%]	[15%]	[20%]	[5%]	[10%]	[15%]	[20%]
P2P loan$_{i,t-1}$	162	149*	158*	200***	36.5	53.8**	42.9*	53.0***	3.70	2.82	2.76	2.44
	(1.27)	(1.67)	(1.82)	(2.66)	(1.13)	(2.31)	(1.91)	(2.71)	(1.37)	(1.49)	(1.50)	(1.54)
Economic magnitude	*83%*	*82%*	*87%*	*110%*	*72%*	*111%*	*91%*	*111%*	*48.6%*	*37.3%*	*37.2%*	*32.5%*
Distance	3,056	1,160	1,052	248	1,571*	-144	125	-70.0	-30.1	-5.40	-14.1	1.57
	(0.87)	(0.85)	(1.36)	(0.51)	(1.76)	(-0.43)	(0.59)	(-0.57)	(-0.40)	(-0.18)	(-0.81)	(0.15)
Distance × Above$_{i,t-1}$	-7,625*	-2,307	-2,282**	-1,567**	-2,843**	-31.2	-428	-241	-25.0	-3.93	19.0	-12.0
	(-1.71)	(-1.23)	(-2.21)	(-2.32)	(-2.48)	(-0.07)	(-1.63)	(-1.51)	(-0.26)	(-0.10)	(0.81)	(-0.85)
Distance sq.	39,880	10,422	8,847*	2,131	32,673*	-895	1,453	-31.3	-939	11.0	-72.3	43.6
	(0.59)	(0.75)	(1.70)	(0.88)	(1.72)	(-0.28)	(0.99)	(-0.05)	(-0.61)	(0.04)	(-0.62)	(0.82)
Distance sq. × Above$_{i,t-1}$	36,688	-6,526	-3,708	3,774	-11,037	459	-280	1,373	1,845	86.6	-19.4	0.66
	(0.35)	(-0.39)	(-0.51)	(1.03)	(-0.41)	(0.12)	(-0.15)	(1.59)	(0.84)	(0.24)	(-0.12)	(0.01)
Borrower FE	No	No	No	No	No	No	No	No	No	No	No	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SE	Robust	Robust	Robust	Robust	Robust	Robust	Robust	Robust	Robust	Robust	Robust	Robust
Observations	467	786	1,082	1,434	478	812	1,127	1,495	483	821	1,139	1,511
Adjusted R^2	0.097	0.029	0.013	-0.020	-0.023	-0.14	-0.060	-0.097	0.057	0.035	0.053	0.073

Table B.6: P2P Lending, Total Debt, and External Access to Credit: RDD – Lagged Outcomes as Controls (IV Stage)

This table reports the results of the second stage of the local fuzzy regression discontinuity design (RDD) regression with an indicator for crossing the funding threshold of 70% as an instrument for the lagged P2P loan origination. The regression is estimated with the inclusion of lagged dependent variables as controls. The regression specification is described by the following two equation system:

$$Y_{ist} = \beta \mathit{P2P\ loan}_{is,t-1} + f(\mathit{Distance}_{is,t-1}) + \mathit{Above}_{is,t-1} \times f(\mathit{Distance}_{is,t-1}) + \eta Y_{is,t-1} + \gamma_s + \delta_t + \epsilon_{ist} \quad \text{(2nd stage)}$$
$$\mathit{P2P\ loan}_{is,t-1} = \phi \mathit{Above}_{is,t-1} + g(\mathit{Distance}_{is,t-1}) + \mathit{Above}_{is,t-1} \times g(\mathit{Distance}_{is,t-1}) + \eta Y_{is,t-1} + \gamma_s + \delta_t + \omega_{ist} \quad \text{(1st stage)}$$

where Y_{ist} is a dependent variable, $Y_{is,t-1}$ is the lagged dependent variable, and $\mathit{Above}_{is,t-1}$ is an instrument in the form of a binary variable equal to one if $\mathit{Distance}_{is,t-1} \geq 0$ and $-h \leq \mathit{Distance}_{is,t-1} \leq h$. The baseline bandwidth h is 10%. The dependent variable *Total debt* is the total balance on all credit accounts. The dependent variable *Revolver limits* is the total credit limit on revolving accounts. The dependent variable *Revolving accounts* is the number of open revolving accounts. The regressor of interest $\mathit{P2P\ loan}_{t-1}$ is the lagged indicator of an originated P2P loan. The instrument Above_{t-1} is an indicator of the funding commitments being at least 70% of the requested loan amount. *Distance* is the difference between the forcing variable (percent funded) and the discontinuity threshold. *Distance sq.* is the squared distance from the discontinuity threshold. The estimates of the intercept, controls, and fixed effects are omitted for brevity. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. T-statistics are presented in parentheses.

Dependent variable:	Total debt ($'000)				Revolver limits ($'000)				Revolving accounts			
10% bandwidth	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
P2P loan$_{t-1}$	17.1	14.7	13.5	32.1	49.9***	45.6***	44.9***	37.2*	-0.34	-0.27	-0.23	-0.15
	(0.75)	(0.70)	(0.66)	(1.11)	(3.15)	(3.07)	(3.03)	(1.95)	(-0.70)	(-0.62)	(-0.53)	(-0.31)
Economic magnitude	*9.4%*	*8.1%*	*7.5%*	*17.7%*	*103.0%*	*94.1%*	*92.7%*	*76.8%*	*-4.5%*	*-3.6%*	*-3.0%*	*-2.0%*
Distance	-44.7	-38.4	12.4	-244	-143***	-134***	-64.2	-34.8	2.57	2.41	0.64	-4.18
	(-0.63)	(-0.58)	(0.14)	(-0.68)	(-2.84)	(-2.78)	(-0.98)	(-0.13)	(1.50)	(1.53)	(0.45)	(-0.64)
Distance × Above$_{t-1}$			-94.8	-40.8			-134	21.0			3.25	12.2
			(-0.63)	(-0.07)			(-1.35)	(0.06)			(1.05)	(1.20)
Distance sq.		-407		-2,564		-739		289		12.2		-48.0
		(-0.57)		(-0.77)		(-1.50)		(0.12)		(0.78)		(-0.76)
Distance sq. × Above$_{t-1}$				4,816				-2,358				2.55
				(0.90)				(-0.83)				(0.03)
Total debt$_{t-1}$	0.85***	0.85***	0.85***	0.84***								
	(22.83)	(22.81)	(22.84)	(22.12)								
Revolver limits$_{t-1}$					0.24**	0.24**	0.24**	0.24**				
					(2.15)	(2.15)	(2.14)	(2.14)				
Revolving accounts$_{t-1}$									0.92***	0.92***	0.92***	0.92***
									(56.55)	(56.46)	(56.48)	(56.56)
Borrower FE	No	No	No	No	No	No	No	No	No	No	No	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SE	Robust	Robust	Robust	Robust	Robust	Robust	Robust	Robust	Robust	Robust	Robust	Robust
Observations	782	782	782	782	806	806	806	806	821	821	821	821
Adjusted R^2	0.84	0.84	0.84	0.84	0.18	0.21	0.21	0.24	0.91	0.91	0.91	0.91

Table B.7: P2P Lending, Total Debt, and External Access to Credit: RDD – Outcomes after First Application (IV Stage)

This table reports the results of the second stage of the local fuzzy regression discontinuity design (RDD) regression with an indicator for crossing the funding threshold of 70% as an instrument for the lagged P2P loan origination. The regression is estimated only for outcomes after the first P2P loan application. The regression specification is described by the following two equation system:

$$Y_{ist} = \beta P2P\ loan_{is,t-1} + f(Distance_{is,t-1}) + Above_{is,t-1} \times f(Distance_{is,t-1}) + \gamma_s + \delta_t + \epsilon_{ist} \quad \text{(2nd stage)}$$

$$P2P\ loan_{is,t-1} = \phi Above_{is,t-1} + g(Distance_{is,t-1}) + Above_{is,t-1} \times g(Distance_{is,t-1}) + \gamma_s + \delta_t + \omega_{ist} \quad \text{(1st stage)}$$

where Y_{ist} is a dependent variable and $Above_{is,t-1}$ is an instrument in the form of a binary variable equal to one if $Distance_{is,t-1} \geq 0$ and $-h \leq Distance_{is,t-1} \leq h$. The baseline bandwidth h is 10%. The dependent variable *Total debt* is the total balance on all credit accounts. The dependent variable *Revolver limits* is the total credit limit on revolving accounts. The dependent variable *Revolving accounts* is the number of open revolving accounts. The regressor of interest *P2P loan*$_{t-1}$ is the lagged indicator of an originated P2P loan. The instrument *Above*$_{t-1}$ is an indicator of the funding commitments being at least 70% of the requested loan amount. *Distance* is the difference between the forcing variable (percent funded) and the discontinuity threshold. *Distance sq.* is the squared distance from the discontinuity threshold. The estimates of the intercept, controls, and fixed effects are omitted for brevity. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. T-statistics are presented in parentheses.

Dependent variable:	Total debt ($'000)				Revolver limits ($'000)				Revolving accounts			
10% bandwidth	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
P2P loan$_{t-1}$	343***	317***	311***	282**	54.0**	51.0**	50.6**	49.7*	0.69	0.57	0.59	1.35
	(3.47)	(3.35)	(3.29)	(2.36)	(2.31)	(2.23)	(2.22)	(1.70)	(0.33)	(0.27)	(0.28)	(0.53)
Economic magnitude	*181%*	*167%*	*164%*	*149%*	*124%*	*117%*	*116%*	*114%*	*8.8%*	*7.3%*	*7.5%*	*17.2%*
Distance	-776**	-694**	-329	71.3	-180**	-171**	-133	-169	2.58	2.95	4.06	-13.9
	(-2.38)	(-2.21)	(-0.75)	(0.04)	(-2.56)	(-2.44)	(-1.31)	(-0.43)	(0.38)	(0.43)	(0.40)	(-0.40)
Distance × Above$_{t-1}$			-695	-816			-74.5	32.4			-2.34	18.3
			(-1.20)	(-0.35)			(-0.61)	(0.06)			(-0.18)	(0.41)
Distance sq.		-3,470		4,005		-415		-375		-17.5		-180
		(-1.16)		(0.23)		(-0.71)		(-0.10)		(-0.27)		(-0.51)
Distance sq. × Above$_{t-1}$				-7,008				-401				148
				(-0.32)				(-0.09)				(0.35)
Borrower FE	No	No	No	No	No	No	No	No	No	No	No	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SE	Robust	Robust	Robust	Robust	Robust	Robust	Robust	Robust	Robust	Robust	Robust	Robust
Observations	562	562	562	562	586	586	586	586	589	589	589	589
Adjusted R^2	-0.16	-0.12	-0.11	-0.077	-0.18	-0.16	-0.15	-0.15	0.070	0.070	0.069	0.053

Table B.8: P2P Lending and FICO Score: RDD (Second Stage)

This table reports the results of the second stage of the local fuzzy regression discontinuity design (RDD) regression with an indicator for crossing the funding threshold of 70% as the (excluded) instrument for the lagged P2P loan origination. The regression tests for jumps in control variables around the discontinuity threshold as a result of treatment. Table 5-A reports the first stage estimates. The regression specification is described by the following two equation system:

$$Y_{ist} = \beta P2P\ loan_{is,t-1} + f(Distance_{is,t-1}) + Above_{is,t-1} \times f(Distance_{is,t-1}) + \gamma_s + \delta_t + \epsilon_{ist} \quad \text{(2nd stage)}$$

$$P2P\ loan_{is,t-1} = \phi Above_{is,t-1} + g(Distance_{is,t-1}) + Above_{is,t-1} \times g(Distance_{is,t-1}) + \gamma_s + \delta_t + \omega_{ist} \quad \text{(1st stage)}$$

where Y_{ist} is a dependent variable, $Above_{is,t-1}$ is an instrument in the form of a binary variable equal to one if $Distance_{is,t-1} \geq 0$ and $-h \leq Distance_{is,t-1} \leq h$. The baseline bandwidth h is 10%. The dependent variable *FICO* [†] is an indicator for a FICO score bin, where the † symbol denotes the range of the bin. The regressor of interest $P2P\ loan_{t-1}$ is the lagged indicator of an originated P2P loan. The instrument $Above_{t-1}$ is an indicator of the funding commitments being at least 70% of the requested loan amount. *Distance* is the difference between the forcing variable (percent funded) and the discontinuity threshold. *Distance sq.* is the squared distance from the discontinuity threshold. The estimates of the intercept and fixed effects are omitted for brevity. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. T-statistics are presented in parentheses.

Dependent variable:	FICO bin										
10% bandwidth	[<640]	[640–659]	[660–679]	[680–699]	[700–719]	[720–739]	[740–759]	[760–779]	[780–799]	[800–819]	[820–850]
P2P loan$_{t-1}$	0.073	0.20	-0.24	0.43	-0.88	-0.10	0.55	0.13	-0.49*	0.27	0.063
	(1.01)	(0.94)	(-0.48)	(0.84)	(-1.50)	(-0.22)	(1.58)	(0.49)	(-1.80)	(1.25)	(0.93)
Distance	-1.30	-3.49	0.21	-7.08	8.12	6.20	-2.61	-1.99	2.95	0.022	-1.02
	(-1.16)	(-1.43)	(0.04)	(-1.54)	(1.57)	(1.36)	(-0.87)	(-0.82)	(1.37)	(0.02)	(-0.97)
Distance × Above$_{t-1}$	0.39	3.37	4.59	6.19	-3.34	-9.37**	0.98	0.27	0.37	-4.05**	0.60
	(0.29)	(1.21)	(0.95)	(1.29)	(-0.62)	(-2.05)	(0.28)	(0.13)	(0.17)	(-2.02)	(0.91)
Distance sq.	-14.6	-35.9	9.53	-82.7**	69.5	78.6*	-15.8	-21.8	20.8	1.27	-8.97
	(-1.26)	(-1.43)	(0.18)	(-2.00)	(1.44)	(1.74)	(-0.56)	(-1.00)	(1.21)	(0.12)	(-0.97)
Distance sq. × Above$_{t-1}$	27.5	49.7	-62.0	76.5	-112	-45.0	22.4	39.6	-52.6	42.9	13.1
	(1.46)	(1.24)	(-0.78)	(1.09)	(-1.36)	(-0.65)	(0.44)	(1.09)	(-1.60)	(1.58)	(0.95)
Borrower FE	No	No	No	No	No	No	No	No	No	No	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SE	Robust	Robust	Robust	Robust	Robust	Robust	Robust	Robust	Robust	Robust	Robust
Observations	471	471	471	471	471	471	471	471	471	471	471
Adjusted R^2	-0.014	-0.044	-0.084	-0.17	-0.68	0.015	-0.68	-0.041	-1.36	-0.24	-0.32

Table B.9: P2P Lending and Other Controls: RDD (Second Stage)

This table reports the results of the second stage of the local fuzzy regression discontinuity design (RDD) regression with an indicator for crossing the funding threshold of 70% as an instrument for the lagged P2P loan origination. The regression tests for jumps in control variables around the discontinuity threshold. Table 5-A reports the first stage estimates. The regression specification is described by the following two equation system:

$$Y_{ist} = \beta P2P\ loan_{is,t-1} + f(Distance_{is,t-1}) + Above_{is,t-1} \times f(Distance_{is,t-1}) + \gamma_s + \delta_t + \epsilon_{ist} \qquad \text{(2nd stage)}$$

$$P2P\ loan_{is,t-1} = \phi Above_{is,t-1} + g(Distance_{is,t-1}) + Above_{is,t-1} \times g(Distance_{is,t-1}) + \gamma_s + \delta_t + \omega_{ist} \qquad \text{(1st stage)}$$

where Y_{ist} is a dependent variable, $Above_{is,t-1}$ is an instrument in the form of a binary variable equal to one if $Distance_{is,t-1} \geq 0$ and $-h \leq Distance_{is,t-1} \leq h$. The baseline bandwidth h is 10%. The dependent variable *Log (income)* is the natural logarithm of monthly income, measured in thousands. The dependent variable *Log (employed)* is the natural logarithm of length of employment, measured in years. The dependent variable *Home owner* is an indicator of home ownership. The dependent variable *Debt-to-income* is the ratio of monthly debt to monthly income. The regressor of interest $P2P\ loan_{t-1}$ is the lagged indicator of an originated P2P loan. The instrument $Above_{t-1}$ is an indicator of the funding commitments being at least 70% of the requested loan amount. *Distance* is the difference between the forcing variable (percent funded) and the discontinuity threshold. *Distance sq.* is the squared distance from the discontinuity threshold. The estimates of the intercept and fixed effects are omitted for brevity. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. T-statistics are presented in parentheses.

Dependent variable: 10% bandwidth	Log (income)	Log (employed)	Home owner	Debt-to- income
$P2P\ loan_{t-1}$	0.70**	1.20*	0.20	0.033
	(2.37)	(1.70)	(0.83)	(0.45)
Distance	-2.83	-12.2	1.83	-0.0048
	(-0.66)	(-1.19)	(0.51)	(-0.00)
Distance × $Above_{t-1}$	5.00	14.5	-5.90	0.089
	(0.90)	(1.11)	(-1.25)	(0.07)
Distance sq.	-7.68	-78.6	4.35	-0.34
	(-0.18)	(-0.83)	(0.12)	(-0.03)
Distance sq. × $Above_{t-1}$	-32.8	17.3	28.6	-1.79
	(-0.63)	(0.14)	(0.68)	(-0.16)
Borrower FE	No	No	No	No
Year FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
SE	Robust	Robust	Robust	Robust
Observations	811	782	821	811
Adjusted R^2	-0.0053	-0.037	0.00054	0.031

Table B.10: P2P Lending, Credit Demand, and Delinquencies – Robustness

This table presents the results of OLS regressions of variables related to credit demand by borrowers on receiving a P2P loan and borrower characteristics based on alternative sample restrictions and definitions of the regressor of interest. Panel A reports the baseline regression. Panel B excludes cancelled applications from the analysis. Panel C excludes applications with 31 or fewer days between them to remove stale credit reports. Panel D uses all subsequent loan applications and an alternative P2P loan variable which is the number of prior P2P loans of the borrower. Panel E uses the baseline P2P loan indicator but uses all subsequent loan applications. The regression specification is as follows:

$$Y_{ist} = \beta P2P\ loan_{is,t-1} + \mathbf{X}_{ist}\zeta + \alpha_i + \gamma_s + \delta_t + u_{ist},$$

The table reports coefficients on $P2P\ loan_{t-1}$ and their economic magnitudes relative to their mean level at the first application. The dependent variable *Revolving balance* is the total balance on revolving accounts. The dependent variable *Revolver utilization* is the ratio of balances to limits on revolving accounts. The dependent variable *Credit card utilization* is the ratio of balances to limits on bank card accounts. The dependent variable *Delinquency* is an indicator of a delinquent borrower. The regressor of interest $P2P\ loan_{t-1}$ is the lagged indicator of an originated P2P loan. All regressions include borrower, state, and year fixed effects as well as controls. Controls include *FICO* bin indicators, *Log (income)*, *Log (employed)*, *Home owner*, and *Debt-to-income*. Standard errors are clustered at the borrower level. All continuous variables are winsorized at the 1^{st} and the 99^{th} percentiles. The estimates of the intercept, controls, and fixed effects are omitted for brevity. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable:	Revolving balance ($'000)	Revolver utilization	Credit card utilization	Delinquency (1/0)
		Panel A: Main specification		
P2P loan (t-1)	-1.45***	-0.050***	-0.059***	-0.0054*
Economic magnitude	*-7.7%*	*-10.3%*	*-10.8%*	*-3.3%*
		Panel B: Cancelled applications excluded		
P2P loan (t-1)	-1.89***	-0.060***	-0.072***	-0.0042
Economic magnitude	*-10.1%*	*-12.4%*	*-13.2%*	*-2.6%*
		Panel C: Stale credit reports excluded		
P2P loan (t-1)	-1.84***	-0.055***	-0.065***	-0.0041
Economic magnitude	*-9.8%*	*-11.3%*	*-11.9%*	*-2.5%*
		Panel D: All subsequent applications - cumulative effect		
P2P loan (t-1)	-1.22***	-0.041***	-0.049***	-0.0045*
Economic magnitude	*-6.5%*	*-8.4%*	*-9.0%*	*-2.7%*
		Panel E: All subsequent applications - marginal effect		
P2P loan (t-1)	-1.10***	-0.035***	-0.039***	-0.000057
Economic magnitude	*-5.9%*	*-7.2%*	*-7.2%*	*0.0%*
Controls:	FICO bin indicators, Log (income), Log (employed), Home owner, and Debt-to-income			
Fixed effects:	Borrower, state, and year			
Standard errors:	Clustered at borrower level			

Table B.11: P2P Lending, Credit Demand, and Delinquencies by Time between Applications

This table presents the results of OLS regressions of variables related to credit demand by borrowers on receiving a P2P loan and borrower characteristics by time between applications. The analysis is restricted to outcomes after the first application. The regression specification is:

$$Y_{ist} = \beta P2P\ loan_{is,t-1} + \mathbf{X}_{ist}\zeta + \alpha_i + \gamma_s + \delta_t + u_{ist},$$

where Y_{ist} is a dependent variable and $\mathbf{X}_{ist}$ is a matrix of controls. The dependent variable *Revolving balance* is the total balance on revolving accounts. The dependent variable *Revolver utilization* is the ratio of balances to limits on revolving accounts. The dependent variable *Credit card utilization* is the ratio of balances to limits on bank card accounts. The dependent variable *Delinquency* is an indicator of a delinquent borrower. The regressor of interest *P2P loan*$_{t-1}$ is the lagged indicator of an originated P2P loan. The economic magnitude of the coefficient of is measured relative to the mean level of the respective dependent variable on previous P2P loan application. Controls include *FICO* bin indicators, *Log (income)*, *Log (employed)*, *Home owner*, and *Debt-to-income*. All continuous variables are winsorized at the 1^{st} and the 99^{th} percentiles. The estimates of the intercept, controls, and fixed effects are omitted for brevity. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. T-statistics are presented in parentheses.

Dependent variable:	Revolving balance ($'000)			Revolver utilization			Credit card utilization			Delinquency (1/0)		
Time (years):	(≤1]	(1–2]	(>2)	(≤1]	(1–2]	(>2)	(≤1]	(1–2]	(>2)	(≤1]	(1–2]	(>2)
P2P loan$_{t-1}$	-1.32***	-1.56***	-2.38	-0.056***	-0.034***	-0.0036	-0.067***	-0.036***	0.018	-0.00062	-0.023***	0.043
	(-9.20)	(-4.60)	(-1.19)	(-21.76)	(-6.36)	(-0.10)	(-21.55)	(-5.48)	(0.39)	(-0.19)	(-2.76)	(0.76)
Economic magnitude	*-7.0%*	*-8.3%*	*-12.7%*	*-11.5%*	*-7.0%*	*-0.7%*	*-12.3%*	*-6.6%*	*3.3%*	*-0.4%*	*-14.0%*	*26.3%*
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Borrower FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Borrower	Borrower	Borrower	Borrower	Borrower	Borrower	Borrower	Borrower	Borrower	Borrower	Borrower	Borrower
Observations	109,476	15,944	850	109,476	15,944	850	109,476	15,944	850	109,476	15,944	850
Adj. within R^2	0.19	0.17	0.18	0.32	0.28	0.21	0.31	0.27	0.21	0.035	0.044	0.066
Adjusted R^2	0.98	0.90	0.79	0.92	0.70	0.48	0.91	0.66	0.45	0.93	0.63	0.50

Table B.12: P2P Lending, Credit Demand, and Delinquencies: Placebo RDD – Second Stage

This table reports the results of the second stage of the placebo local fuzzy regression discontinuity design (RDD) regression with an indicator for crossing the placebo funding threshold of 70% as the (excluded) instrument for the lagged placebo P2P loan origination. The placebo RDD is estimated based on a subsample of borrowers not subject to the 70% funding threshold. Table B.4-A reports the first stage estimates. The regression specification is described by the following two equation system:

$$Y_{ist} = \beta P2P\ loan_{is,t-1}(placebo) + f(Distance_{is,t-1}) + Above_{is,t-1} \times f(Distance_{is,t-1}) + \gamma_s + \delta_t + \epsilon_{ist} \qquad \text{(2nd stage)}$$

$$P2P\ loan_{is,t-1}(placebo) = \phi Above_{is,t-1} + g(Distance_{is,t-1}) + Above_{is,t-1} \times g(Distance_{is,t-1}) + \gamma_s + \delta_t + \omega_{ist} \qquad \text{(1st stage)}$$

where Y_{ist} is a dependent variable, $Above_{is,t-1}$ is an instrument in the form of a binary variable equal to one if $Distance_{is,t-1} \geq 0$ and $-h \leq Distance_{is,t-1} \leq h$. The baseline bandwidth h is 10%. The dependent variable *Revolving balance* is the total balance on revolving accounts. The dependent variable *Revolver utilization* is the ratio of balances to limits on revolving accounts. The dependent variable *Credit card utilization* is the ratio of balances to limits on bank card accounts. The dependent variable *Delinquency* is an indicator of a delinquent borrower. The regressor of interest $P2P\ loan_{t-1}(placebo)$ is the lagged indicator of the placebo P2P loan origination which equals to 1 if the loan application was above the threshold and expired and 0 if the loan application was cancelled or withdrawn. The instrument $Above_{t-1}$ is an indicator of the funding commitments being at least 70% of the requested loan amount. *Distance* is the difference between the forcing variable (percent funded) and the discontinuity threshold. *Distance sq.* is the squared distance from the discontinuity threshold. The estimates of the intercept and fixed effects are omitted for brevity. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. T-statistics are presented in parentheses.

Dependent variable:	Revolving balance ($'000)				Revolver utilization				Credit card utilization				Delinquency (1/0)			
10% bandwidth	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
P2P loan$_{t-1}$ (placebo)	0.38	0.13	0.079	-3.71	0.0073	0.009	0.0081	-0.015	-0.016	-0.009	-0.011	-0.014	-0.009	0.0019	0.0031	-0.051
	(0.11)	(0.04)	(0.02)	(-0.72)	(0.21)	(0.27)	(0.24)	(-0.29)	(-0.41)	(-0.24)	(-0.28)	(-0.24)	(-0.19)	(0.04)	(0.07)	(-0.71)
Distance	15.8	18.3	3.07	55.2	-0.22	-0.24	-0.18	-0.36	-0.19	-0.25	0.037	-0.91	-0.31	-0.41	0.13	1.85
	(0.64)	(0.73)	(0.09)	(0.40)	(-0.87)	(-0.93)	(-0.53)	(-0.26)	(-0.66)	(-0.89)	(0.09)	(-0.57)	(-0.90)	(-1.20)	(0.28)	(1.02)
Distance × Above$_{t-1}$			31.3	133			-0.088	1.54			-0.55	1.56			-1.10	-1.66
			(0.59)	(0.63)			(-0.16)	(0.73)			(-0.90)	(0.65)			(-1.51)	(-0.57)
Distance sq.		126		520		-0.87		-1.71		-3.26		-9.27		-4.68		17.0
		(0.50)		(0.40)		(-0.33)		(-0.13)		(-1.10)		(-0.61)		(-1.33)		(0.97)
Distance sq. × Above$_{t-1}$				-2,110				-13.2				-2.55				-29.1
				(-0.98)				(-0.62)				(-0.11)				(-1.01)
Borrower FE	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SE	Robust	Robust	Robust	Robust	Robust	Robust	Robust	Robust	Robust	Robust	Robust	Robust	Robust	Robust	Robust	Robust
Observations	1,645	1,645	1,645	1,645	1,645	1,645	1,645	1,645	1,695	1,695	1,695	1,695	1,855	1,855	1,855	1,855
Adj. R^2	0.019	0.018	0.019	0.017	0.034	0.034	0.034	0.032	0.015	0.015	0.015	0.014	0.11	0.11	0.11	0.11

Table B.13: P2P Lending, Credit Demand, and Delinquencies: RDD – Robustness to Bandwidth (IV Stage)

This table reports the results of the second stage of the local fuzzy regression discontinuity design (RDD) regression with an indicator for crossing the funding threshold of 70% as an instrument for the lagged P2P loan origination for various bandwidths. The regression specification is described by the following two equation system:

$$Y_{ist} = \beta P2P\ loan_{is,t-1} + f(Distance_{is,t-1}) + Above_{is,t-1} \times f(Distance_{is,t-1}) + \gamma_s + \delta_t + \epsilon_{ist} \quad \text{(2nd stage)}$$

$$P2P\ loan_{is,t-1} = \phi Above_{is,t-1} + g(Distance_{is,t-1}) + Above_{is,t-1} \times g(Distance_{is,t-1}) + \gamma_s + \delta_t + \omega_{ist} \quad \text{(1st stage)}$$

where Y_{ist} is a dependent variable, $Above_{is,t-1}$ is an instrument in the form of a binary variable equal to one if $Distance_{is,t-1} \geq 0$ and $-h \leq Distance_{is,t-1} \leq h$. The baseline bandwidth h is 10%. The dependent variable *Revolving balance* is the total balance on revolving accounts. The dependent variable *Revolver utilization* is the ratio of balances to limits on revolving accounts. The dependent variable *Credit card utilization* is the ratio of balances to limits on bank card accounts. The dependent variable *Delinquency* is an indicator of a delinquent borrower. The regressor of interest $P2P\ loan_{t-1}$ is the lagged indicator of an originated P2P loan. The instrument $Above_{t-1}$ is an indicator of the funding commitments being at least 70% of the requested loan amount. *Distance* is the difference between the forcing variable (percent funded) and the discontinuity threshold. *Distance sq.* is the squared distance from the discontinuity threshold. The estimates of the intercept and fixed effects are omitted for brevity. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. T-statistics are presented in parentheses.

Dependent variable:	Revolving balance ($'000)				Revolver utilization				Credit card utilization				Delinquency (1/0)			
Bandwidth:	[5%]	[10%]	[15%]	[20%]	[5%]	[10%]	[15%]	[20%]	[5%]	[10%]	[15%]	[20%]	[5%]	[10%]	[15%]	[20%]
P2P loan$_{t-1}$	14.1	29.3**	29.0**	31.6***	0.049	0.29**	0.30**	0.24**	0.15	0.35**	0.34**	0.33***	0.19	0.094	-0.056	-0.033
	(0.71)	(2.11)	(2.21)	(2.79)	(0.27)	(2.11)	(2.31)	(2.20)	(0.76)	(2.41)	(2.50)	(2.82)	(0.81)	(0.51)	(-0.30)	(-0.20)
Economic magnitude	*59.8%*	*137.9%*	*136.3%*	*140.1%*	*10.3%*	*61.9%*	*64.5%*	*52.1%*	*30.4%*	*70.5%*	*69.5%*	*68.3%*	*110.8%*	*55%*	*-30%*	*-18%*
Distance	1,178**	36.0	99.7	31.7	8.14	-2.26	-1.24	-0.20	5.99	-2.60	-1.78	-0.62	-12.1*	-1.76	1.69	-0.34
	(2.38)	(0.18)	(0.87)	(0.45)	(1.51)	(-1.08)	(-1.09)	(-0.28)	(1.03)	(-1.17)	(-1.48)	(-0.82)	(-1.66)	(-0.66)	(1.06)	(-0.34)
Distance × Above$_{t-1}$	-1,608**	-85.6	-280*	-187*	-4.37	3.22	0.98	0.066	-3.27	3.96	2.21	0.14	14.7	0.64	-3.31	0.86
	(-2.41)	(-0.31)	(-1.83)	(-1.91)	(-0.73)	(1.21)	(0.67)	(0.07)	(-0.50)	(1.38)	(1.40)	(0.14)	(1.61)	(0.18)	(-1.62)	(0.66)
Distance sq.	23,545**	503	909	401	181*	-18.3	-7.79	0.12	132	-16.9	-10.9	-1.99	-268*	-25.9	11.8	-2.43
	(2.42)	(0.27)	(1.13)	(1.11)	(1.65)	(-0.90)	(-1.06)	(0.03)	(1.14)	(-0.79)	(-1.40)	(-0.55)	(-1.80)	(-1.03)	(1.13)	(-0.53)
Distance sq. × Above$_{t-1}$	-17,259	-1,354	-80.2	229	-273*	4.74	9.37	-0.26	-201	-0.62	5.34	3.44	186	32.4	4.88	0.85
	(-1.13)	(-0.60)	(-0.07)	(0.42)	(-1.91)	(0.20)	(0.93)	(-0.05)	(-1.32)	(-0.02)	(0.49)	(0.65)	(0.93)	(1.05)	(0.35)	(0.13)
Borrower FE	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SE	Robust	Robust	Robust	Robust	Robust	Robust	Robust	Robust	Robust	Robust	Robust	Robust	Robust	Robust	Robust	Robust
Observations	483	821	1,139	1,511	483	821	1,139	1,511	483	821	1,139	1,511	483	821	1,139	1,511
Adj. R^2	0.022	-0.092	-0.074	-0.066	0.040	-0.075	-0.051	-0.030	0.057	-0.034	-0.018	-0.030	-0.040	-0.011	0.0008	-0.003