

Financial Intermediary Competition, Information  
Acquisition and Moral Hazard: Evidence from  
Peer-to-peer Lending Platforms

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## Abstract

I use unique datasets from peer-to-peer lending platforms and a platform entry event to study competition among financial intermediaries. Under competition, the risk-adjusted interest rate decreases for safe borrowers but increases for risky borrowers, and the incumbent platform becomes less prudent in borrower screening, and the corresponding loan performance is aggravated. Competition distorts the intermediaries' incentive between borrowers and lenders through two channels. Competition reduces intermediaries' incentive to acquire information on borrowers, allowing more lemon problems. In addition, with higher interest rates on the risky borrowers, the incumbent takes less position with her own capitals, and thus becomes less prudent in borrowers' screening. I estimate the welfare change to this market induced by intermediary competition.

MARK BAUM: *Have you ever refused to rate any of these bonds upper-tranches AAA? Can you name one time in the past year, where you checked the tape and you didn't give the banks the AAA-percentage they wanted?*

GEORGIA: *If we don't give them the ratings, they'll go to Moody's right down the block. If we don't work with them, they will go to our competitors. Not our fault. Simply the way the world works.*

—The Big Short (2015): Mark Baum and Georgia from S&P

## 1 Introduction

Financial intermediaries are more efficient at capital allocation and market-making than non-intermediated bilateral trades, similar to other platforms in a two-sided market (Rochet and Tirole (2006)). In addition, they also serve as delegated monitors and information producers to avoid lemons and moral hazard problems (Campbell and Kracaw (1980)). This paper studies how competition affects the incentives of financial intermediaries on both asset pricing and information production. Moreover, how does competition affect the welfare of either side of the market?

On one hand, theoretical literature has suggested that competition reduces financial intermediaries' prudent behavior by various mechanisms, such as moral hazards and adverse selections.<sup>1</sup> Bolton et al. (2012) models the conflict of interest among competing

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<sup>1</sup>Sharpe (1990) argues that competition undermines relationship banking and drives banks to explore new and unfamiliar customers, which lowers loan performances due to information asymmetry. Keeley (1990) argues that competition induces banks' moral hazard. Banks compete for market share by taking on risky projects, and alleviate the downside risk by purchasing deposit insurance. Hauswald and Marquez (2006) show that competition reduces banks' incentive to acquire information on borrowers,

credit rating agencies (CRAs), investors and bond issuers. They show that due to issuers' preference on rate shopping and investors' trusting nature, credit rating agencies shift their interest towards the issuers and away from the investors under competition. On the other hand, literature has also addressed that competition among financial intermediaries is crucial to economic growth and entrepreneurial activities.<sup>2</sup> Other theories suggest that an absence of competition leads to high interest rates which induce entrepreneurs' risk-taking behavior.<sup>3</sup>

Most empirical literature lack exogeneity and data granularity, and no empirical literature documents both sides of the trade-offs. Beck et al. (2003) and Beck et al. (2013) use country level data and document a strong positive correlation between banking-industry competition and economic fragility.<sup>4</sup> Becker and Milbourn (2011) study the natural experiment where Fitch enters to compete with S&P and Moody's in credit rating. They find that the incumbents lowered their rating quality by offering a higher rating level *ceteris paribus*, and as a consequence, both loan market yield and default predictive power fell. Although their paper provides a strong and exogenous prediction on how competition affects intermediaries' incentive and creditors' welfare, they do not shed light upon how competition benefits the debtors. Using data from U.S. local banking markets, Cetorelli and Strahan (2006) show that potential entrepreneurs face greater difficulty gaining ac-

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allowing for more lemon problems. See other papers such as Hellmann et al. (2000) on competition, risk taking and capital requirement; Marquez (2002) on information dispersion and adverse selection due to competition; Broecker (1990) on lower credit-worthiness caused by competition. Some theories suggest otherwise.

<sup>2</sup>Allen and Gale (1998) argue that perfect financial stability may be socially undesirable, and can lead to inefficient outcome.

<sup>3</sup>Boyd and De Nicolo (2005) argue that under a general equilibrium environment, entrepreneurs tend to choose risky projects when the banking industry is concentrated and capitals are expensive.

<sup>4</sup>Beck et al. (2003) examine data from 79 countries, and find that crises appear to be less likely in more concentrated banking systems. Similarly Beck et al. (2013) use cross-country data and find that competition causes economic fragility, and it appears that the effect is more severe in countries with more generous deposit insurance and better credit information sharing.

cess to credit where banking is less competitive. I use an exogenous variation on the market structure of financial intermediaries and document the trade-offs of financial intermediary competition from both sides. How does competition affect the intermediaries' incentives and both creditors' and debtors' welfare?<sup>5</sup>

Other papers argue that contracts can eliminate agency problems and banking failure.<sup>6</sup> In practice, financial intermediaries such as shadow banking are not under regulation by agencies such as FDIC. Covenants or collaterals are also not feasible in many financing vehicles. By studying the trade-offs of financial intermediaries' competition, this paper provides a non-structural preliminary welfare implication on the market structure of financial intermediaries.

In this paper, I use loan-level data from online peer-to-peer lending platforms. A peer-to-peer lending platform is a type of financial intermediary, where it screens and classifies the borrowers, aggregates and produces information from them, posts interest rates on the loans, and attracts lenders nationwide. The lenders observe the interest rates and borrower characteristics and credit history, and make decision. I incorporate data of both loans originated and rejected from the duopoly peer-to-peer lending platforms, LendingClub and Prosper. Using an exogenous event study on Prosper's entry which tightens the platform-level competition, I find strong empirical evidence that LendingClub, the incumbent, degrades its screening mechanism, allowing more risky borrowers financed. I find that post-entry loan performance on the incumbent is aggravated. Evidence shows that competition destructs the intermediaries' incentive to acquire high-quality informa-

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<sup>5</sup>Allen and Gale (2004) argue the optimality of this trade off, but lacked empirical support.

<sup>6</sup>Diamond and Dybvig (1983) on deposit insurance and bank runs, Egan et al. (2015) and Hellmann et al. (2000) on financial stability and capital requirements, Smith and Warner (1979) on bond covenants and Berger and Udell (1990) on collaterals.

tion. In the meantime, I find the interest rates are lowered for the safe borrowers by the incumbent but raised for the risky ones after the entry. This finding is consistent with the intermediaries' incentive on balancing between lenders' and borrowers' payoffs. Combining data from both platforms, I find a higher growth of applicants who gain the access to financing after the entry. The market expansion indicates more economic activities.

Motivated by the empirical result, I provide a theoretical model where banks have less incentive to acquire information in a more competitive market. From a monopoly framework to Bertrand competition, I show that the quality of information acquired on borrowers deteriorates in equilibrium. Following the model, I estimate the welfare change induced by the competition to both borrowers and lenders.

## **2 Institutional Background**

### **2.1 Institution Details of Peer-to-peer Lending in U.S.**

#### **2.1.1 Institutional Summary**

Peer-to-peer lending is a type of profit-seeking crowdfunding, serving as a platform where lenders and borrowers match. All peer-to-peer lending platforms operate online and use debt as the financing instrument.<sup>7</sup> Since the commencement of this new financing intermediary in 2005 in U.S., the accrued loan volume issued reached \$25 Billion, leading the U.S. online alternative finance industry.<sup>8</sup> During the year of 2014 alone, it accounts for \$5.5 Billion loans issued, and according to PwC's estimation, this figure could reach

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<sup>7</sup>Other types of crowdfunding include donation (Donorschoose), product reward (Kickstarter), and also equity (AngelList).

<sup>8</sup>The Americas alternative finance benchmarking report, 2016.

150 Billion annually.<sup>9</sup>

There are two major platforms operating within U.S., LendingClub and Prosper, accounting for 98% of the peer-to-peer lending market.<sup>10</sup> According to data from the platforms, more than 80% of the loans issued are claimed to be used for personal debt consolidation in 2015.<sup>11</sup>

### **2.1.2 Market Agents and Market Mechanism**

Four types of agents participate in this market, borrowers, lenders, platforms and platform-partnered banks. Since their establishments, both LendingClub and Prosper operate alongside with WebBank, an FDIC-insured Utah-chartered Industrial Bank.<sup>12</sup> WebBank plays two important roles for LendingClub and Prosper. First, WebBank has easy access to borrowers' credit reports, and thus may better acquire information understand borrowers' creditworthiness. Second, WebBank is the entity that underwrites the loans, and holds on to them until the lenders purchase them.<sup>13</sup> However, WebBank does not participate in lending itself.

Any adult U.S. resident with a social security may apply for an unsecured loan less than \$35,000 on a peer-to-peer lending platform. A loan application requires the borrower's social security number, her current employment status and income, her home-ownership, the intended term of the loan (3-year or 5-year) and the requested loan size.

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<sup>9</sup>PwC 2015, Peer Pressure.

<sup>10</sup>According to an Economist article in 2014, "Peer-to-Peer Lending: Banking without Banks".

<sup>11</sup>However, the loans are not covenanted, and thus the usage of credit is not enforced. Based on LendingClub's description, the products includes personal loans and small business loans (greater than \$35,000). All loans exceeding \$35K are secured (collateralized) but the data is not disclosed, and thus will not be further discussed.

<sup>12</sup>See Prosper Lender Registration Agreement and LendingClub Prospectus. Also, see "Where Peer-to-Peer Loans Are Born", Bloomberg.

<sup>13</sup>See 'WebBank And Alt Lending's 'Perfect Storm', by pymts.

The platform (and the partnered bank) review the borrower's application. They acquire the borrower's credit report to observe her FICO score, current debt outstanding, recent delinquencies and default history from credit agencies.<sup>14</sup> Then they verify the information on the borrower's employment status, income and homeownership. Based on those and other measures they compute, such as debt to income ratio, they decide whether to grant the borrower a loan.<sup>15</sup> If a loan is granted, based on the borrower credit history and her intended loan contract, the platform evaluates her risk and classifies her into a rating category.<sup>16</sup> A rating is mapped to an interest rate, becoming a take-it-or-leave-it contract offer back to the borrower. If the borrower accepts the interest rate offer, her loan will be posted on the platform's website along with her credit information to attract financing.

The listing period for a loan is typically limited up to 14 days.<sup>17</sup> Each loan is typically split into securities of \$25 called notes, and lenders observe the loan contracts and the borrowers' credit history, and choose the number of notes to invest in.<sup>18</sup> A loan will be issued as soon as it's been filled by the lenders. If the lenders' pledged amount exceeds 60% of the requested at expiration, the borrower can choose either to keep the funded amount under the same interest rate, or to reject the loan and refund the lenders.<sup>19</sup> Under any other cases, the loan will be dropped.<sup>20</sup> If a loan gets issued, the platform

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<sup>14</sup>LendingClub claims to pull one or more credit reports from credit agencies such as Transunion, Experian and Equifax, whereas Prosper pulls data from Experian.

<sup>15</sup>Both LendingClub and Prosper claim that they only accept prime borrowers. LendingClub strictly rejects any borrower with FICO score below 640 and for Prosper, it is 600.

<sup>16</sup>For LendingClub, the rating spectrum ranges over 35 categories. For Prosper, the rating is coarser, 7 categories.

<sup>17</sup>Before Dec, 2010, listing on Prosper was 7 days.

<sup>18</sup>Institutional Investors tend to invest in whole loans than a fraction. See 'Wall Street is hogging the peer-to-peer lending market', QUARTZ.

<sup>19</sup>It is 60% for LendingClub and 70% for Prosper.

<sup>20</sup>As the underwriter, WebBank is the loan issuer. The platform plays a role as a dealer between WebBank and the lenders, where the lenders deposit the fund to the platform, which later is transferred

directly profits a percentage fee, usually 1% - 5%, of the issued amount, leaving the residual for the borrower.<sup>21</sup> Although platforms do not disclose much information on their lenders, currently institutional investors chipped in more than 80% in peer-to-peer lending platforms.<sup>22</sup>

The loan repayment process is implemented on the platform, and identical to a mortgage, gets amortized monthly. Borrowers are expected to follow the payment schedule until the term ends.<sup>23</sup> A borrower may be delinquent on her loan, if a payment is delinquent more than 150 days, the loan is defaulted (charged-off). A default negatively affects the borrower's credit report and future borrowing ability. Defaulted loans are later sold to collection agencies for recovery.

### **2.1.3 Comparison to Traditional Financing**

Compared to other financial intermediaries such as banking and credit rating agencies, peer-to-peer lending is similar because it produces information on borrowers, screens them and prices the interest rates. The fundamental difference between banks and peer-to-peer lending is that banks take position, like dealers in an over-the-counter market, whereas peer-to-peer lending platforms do not, similar to brokers.<sup>24</sup>

Not being a perfect substitute of banking, peer-to-peer lending still exists in the shadow of consumer banking. Some suggest that peer to peer lending isn't a threat to

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to WebBank.

<sup>21</sup>For example, for a loan of \$1,000 with fee 5%, the platform receives \$50 loan origination fee at the time of loan issuance. The borrower receives \$950 capital, but the principal on the loan stays at \$1,000.

<sup>22</sup>Historically, Prosper disclosed information on lenders for each loan until late 2013. According to LendingClub, an institution can be banks, pension funds, asset management companies, etc. See 'The Evolving Nature Of P2P Lending Marketplaces', Techcrunch.

<sup>23</sup>Borrower first repay the platform, and the payments will be later transformed back to the lenders. Borrowers can pay off the loan early without punishment.

<sup>24</sup>Due to this feature, banks are subject to liquidity shocks, where capital requirements and deposit insurance are enforced. Hellmann et al. (2000), Allen and Gale (2000) and Diamond and Dybvig (1983)

the banking industry, while others claim it may be the future of banking and the credit market.<sup>25</sup> On the borrowing side, bank and their borrowers both benefit from and can heavily rely on relationship, where borrowers access to cheaper credit and their banks in return gets a lower default rate (Agarwal et al. (2009)). Moreover, Agarwal et al. (2009) show that 56% of accounts in their sample are 'Relationship Accounts'. In contrast, based on the data provided by Prosper, although once repeated borrower propensity spiked to 45% in 2011, the number stays around 20%-30%.<sup>26</sup>

Second, peer-to-peer lending targets a special niche of borrowing market and may undercut banks. Shown by data, dominated by personal loans, the claimed purposes of the loans are for debt consolidation.<sup>27</sup> A borrower facing a higher interest rate from a bank or a credit card debt looks for a loan with lower interest on a peer-to-peer lending platform. According to the Fed, conditional on that a credit card loan has been granted, the average interest rate on it is between 13-14% (APR) in 2014. On LendingClub alone, conditional on a FICO score 750 and above, the average interest rate is 8.4%. Moreover, across all loans on LendingClub, controlled for loan contract terms and borrower credit history, a loan with claimed purpose as 'debt consolidation' is 2.4% cheaper than 'small business'. Loans from a commercial bank such as auto-loan or student-loan are secured loan with cheaper interest rate (4% APR) than peer-to-peer lending, while incomparable since loans under \$35,000 do not require collateral on all peer-to-peer lending platforms.

On the lender side, banks and deposit institutions provide deposit insurance, and thus guarantees safe returns for depositors. However, the average deposit interest rate is less

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<sup>25</sup>See 'Peer-to-peer lenders will never challenge the banks, says Deloitte', The Telegraph. See 'Lending Club Can Be a Better Bank Than the Banks', Bloomberg.

<sup>26</sup>'Is the Surge of Repeat Borrowers at Prosper Over?', Lendacademy

<sup>27</sup>Business loans on peer-to-peer lending are booming. See 'How Lending Club Is Shaping the Future of Small-Business Loans', Inc.

than 0.5% for a 3-year CD, according to Fed, much lower than the current adjusted annual return from LendingClub, between 4.9% and 8.3%. Other than individual investors, large institutions such as banks and funds account for more than 80% of the loan volume. Citigroup just announced their partnership with LendingClub.<sup>28</sup> As a fast growing financing phenomenon that is more and more connected with the banking industry on both borrowing and lending sides, it is important to study the competition within the peer-to-peer lending industry.

## **2.2 Institutions: LendingClub vs. Prosper**

Only operating within U.S, LendingClub is currently the world's largest profit-seeking crowdfunding and the largest peer-to-peer lending platform, followed by Prosper.com, its biggest competitor.<sup>29</sup> By 2015, LendingClub has raised a total of \$15.98 billion in loans, compared to Prosper's \$6 billion.

### **2.2.1 LendingClub**

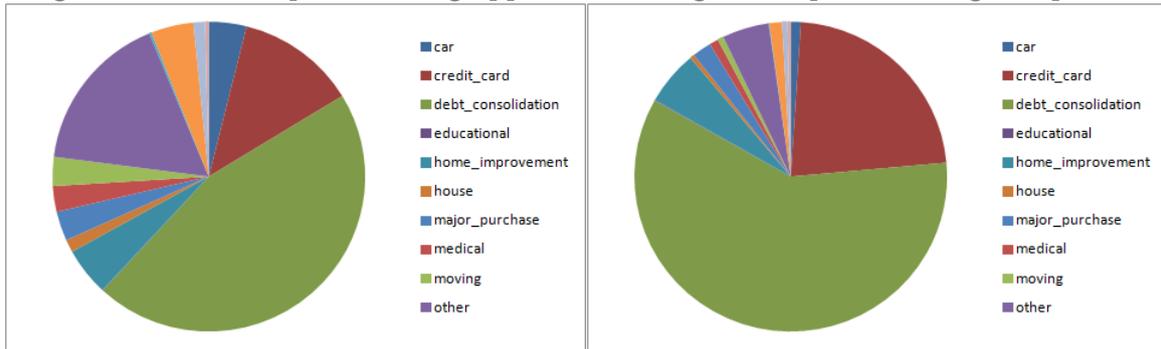
Since its founding in 2007, LendingClub had accepted 646,389 among 5,317,010 loan applications by the end of 2014. With more than 55% of the loan applications going for debt consolidations/credit card, the proportion is over 80% among the issued loans. Other major purposes include car financing, educational, housing and home improvement, purchases, medical, small business, vacation, wedding, etc. (see Figure 1). Without collateral, LendingClub claims to target prime borrowers with FICO score above 640. Other

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<sup>28</sup>'This Huge Bank Is Coming to Lending Club's Rescue.' Fortune

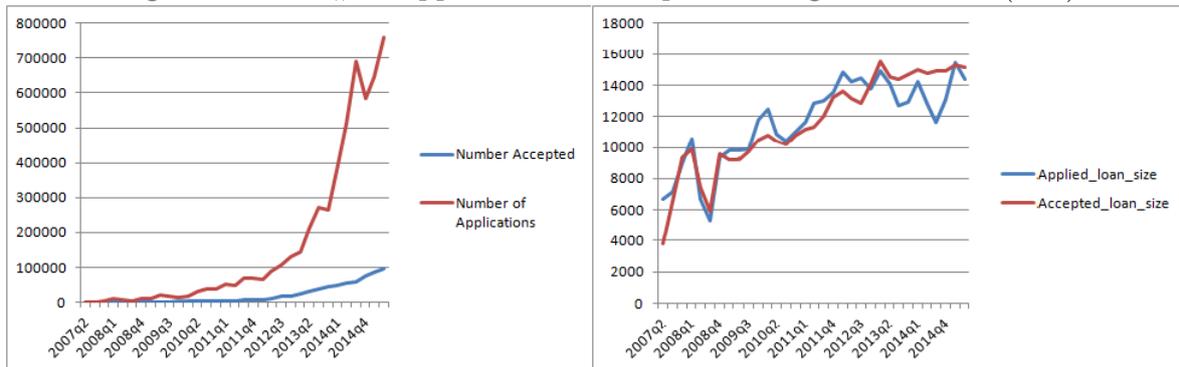
<sup>29</sup>LendingClub currently accepts borrowers in all states but Iowa and West Virginia and lenders in all but Ohio, Pennsylvania, New Mexico, North Carolina and Hawaii. Other platforms such as Academic Capital Exchange, CapAlly, GreenNote, and so on have joined the market recently.

Figure 1: Left: Purposes among applications. Right: Purposes among acceptances



selection criteria include borrowers' incomes, employment lengths, debt-to-income ratios, FICO scores, credit history such as recent delinquencies and defaults, requested loan size, intended loan purposes and loan term.<sup>30</sup> An initial screening determines borrowers' acceptances (see Figure 2). Upon approval, LendingClub further classifies them into 35

Figure 2: Left: # of application vs acceptance. Right: loan size (in \$)



different 'Grades' ordering from A1, A2, A3, A4, A5, B1... G5 by its own risk measurement, where A1 is the safest and G5 is the riskiest. Each category is associated with one interest rate at any snapshot in time. Table 1 shows the monthly interest rates and loan origination fees corresponding to each 'Grade' category. As aforementioned, each loan is divided into notes of \$25 and posted on LendingClub.com for up to 14 days.<sup>31</sup> An aver-

<sup>30</sup>A loan can either have a term of 3 or 5 years. Short term loans are available on Prosper.

<sup>31</sup>For example, a loan of \$10,000 will be divided into 400 notes, and each note is worth \$25. The loan will be delisted from the website as soon as fully funded. If the pledged amount fails to achieve the 60% of the requested amount, the loan will be dropped and returned to the lenders.

Table 1: Monthly Interest Rates and Origination Fees on LendingClub in 2015

Loan Grade	A	B	C	D	E	F	G
Interest Rate	0.44 ~0.66%	0.68 ~0.96%	1.02 ~1.22%	1.30 ~1.49%	1.52 ~1.75%	1.83 ~2.15%	2.23 ~2.42%
Origination Fee	1~4%	4~5%	5%	5%	5%	5%	5%

Table 2: Numbers of Accepted Loans Across Year and Grades (2007-2015/06)

	A	B	C	D	E	F	G
2007	57	61	75	37	14	7	0
2008	295	507	438	222	75	21	4
2009	1,178	1,365	1,193	657	236	64	23
2010	2,709	3,284	2,293	1,472	663	200	72
2011	5,665	5,811	3,279	2,259	1,296	527	159
2012	7,667	12,010	7,799	4,766	1,953	831	174
2013	5,645	16,172	14,544	8,762	3,875	2,055	417
2014	4,107	8,580	10,310	7,389	3,988	1,506	448

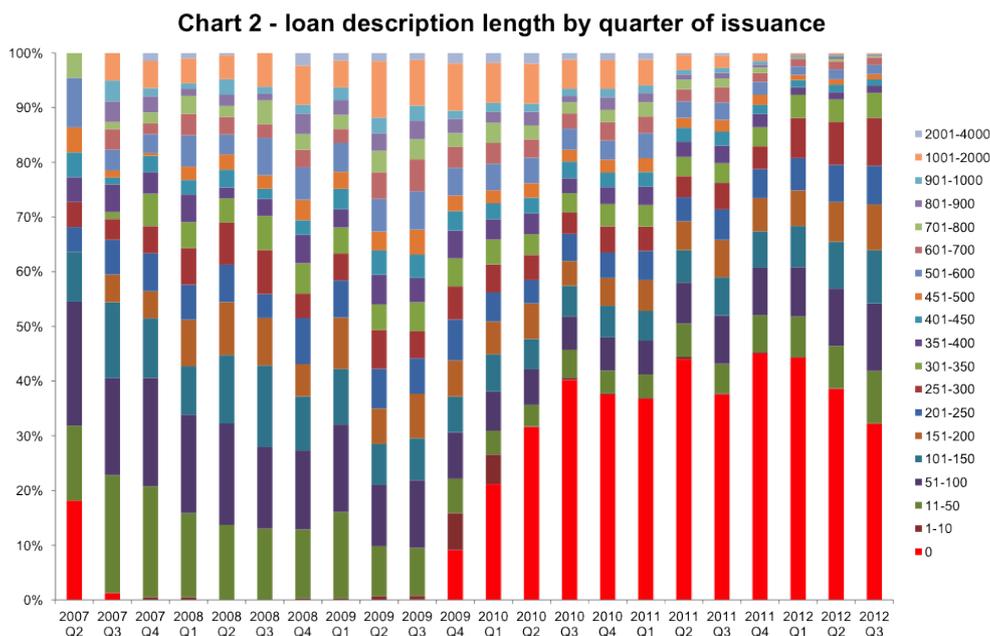
age lender on LendingClub observes all the currently listed loan contracts. Each listing captures the borrower's requested loan size, current funded amount and instantaneous number of lenders, loan term, listing expiration date, its intended purpose, the grade assigned by LendingClub and the interest rate.<sup>32</sup> Observable borrower characteristics include her zipcode at county-level, employment length, title and annual income. Observable borrower credit history features debt-to-income ratio, recent FICO score range, delinquency record within the last two years, credit card revolver balance and utilization, default history, and collections. For loans issued before Sep, 2009, almost all listings include descriptions entailing their usage of the loan, current financial situation and answers to questions from the lenders.<sup>33</sup> Absences of loan descriptions or descriptions with

<sup>32</sup>All loans that were issued before 2010 only had 3-year maturity.

<sup>33</sup>One borrower applied a loan in Nov,2008 described his loan purpose as follows. "I am applying for this loan because I am trying to lower my credit card so I can start saving up some money. I graduated college two years ago and have had my current job for about a year and a half. I just moved home, (so no rent/bills- thanks mom and dad!) and I don't have a whole lot of other expenses. With some frugal months I could have this paid off, but I am getting married in about ten months and have been slammed with deposits, and a big dental bill for \$3,000, virtually eliminating my savings. My parents are paying for the "big stuff" for the wedding, but I have been picking up the deposits. So, I am not in any way concerned with having to pay a few hundred dollars a month, I just would like to not be paying that high interest rate and would like to be saving some money on my end. No credit card debt with a steady

10 characters less largely emerge in the 4th quarter of 2009. Data shows that the propensity of a borrower comments or describe her loan went down to nearly 50% in 2010. An anecdotal research also show this phenomenon (see Figure 3).<sup>34</sup> The reason for this event was not disclosed by LendingClub.

Figure 3: Loan Descriptions Length (in characteristics) with Vintage 2007-2012



According to data and former CEO, LendingClub has also provided funding to loans listed on its website.<sup>35</sup> The amount pledged by LendingClub on each loan was not observable by lenders but provided in data.

Shown by LendingClub's data, for loans with vintage prior to 2010, the net annual-

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amount at a lower interest rate is what I am hoping for. A monthly payment would be easily managed." See [https://www.lendingclub.com/browse/loanDetail.action?loan\\_id=364451](https://www.lendingclub.com/browse/loanDetail.action?loan_id=364451)

<sup>34</sup>Figure 3 is from an article describing research conducted by Sam Kramer on Lending Academy. <http://www.lendacademy.com/lending-club-loan-descriptions-1/>

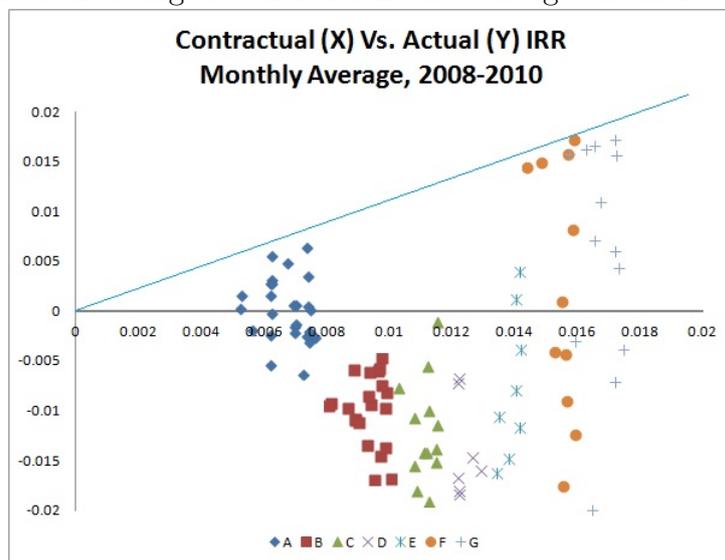
<sup>35</sup>It largely happened during the period when LendingClub was under evaluation by SEC in 2008. See 'A Look Back at the Lending Club and Prosper Quiet Periods', Lending Academy. However, even before and after the 'quiet' period, LendingClub has also lent to its borrowers.

Former CEO also told Wall Street Journal that LendingClub slowed down its activity in the 'quiet' period to use its own money to fund borrowers. "Peer-To-Peer Lenders Get Into Secondary Market", WSJ.

This is one key institutional differences between LendingClub and Prosper, where Prosper has not played the role as a lender.

ized return stay between 5% to 7% across all the loan grades. Figure 4 illustrates the contractual vs. the actual returns measured by the internal rate of return (IRR) for loans with vintage between 2008 and 2010 aggregated at monthly level, where the blue line is a 45° line. Although the graph shows average negative returns for grade B, C and D, the measure IRR are highly left skewed for unpaid and defaulted loans. Since the data is aggregated to monthly level, no stochastic dominance can be inferred. However, on average grade A outperforms B,C,D using the IRR measure.

Figure 4: LendingClub:IRR for Loans Vintaged from 2008-2010



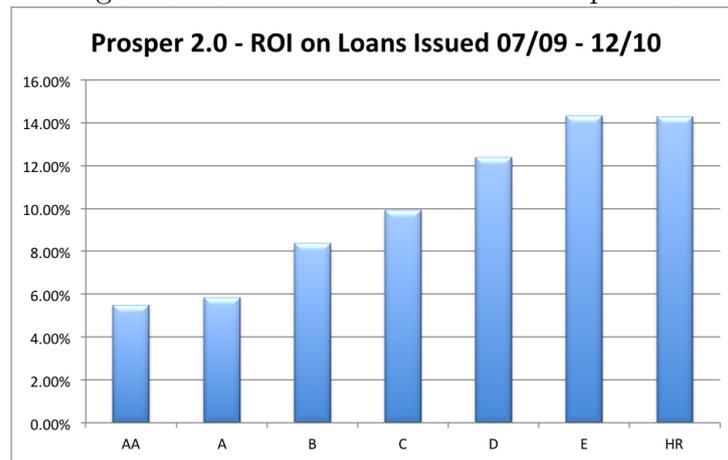
### 2.2.2 Prosper and Re-entry

Founded in 2005, two years before LendingClub, Prosper started with peer-to-peer lending in U.S. under an auction model.<sup>36</sup> Prior to Oct, 2008, having accepted borrowers any all

<sup>36</sup>The auction mechanism works as follows. Besides the purpose, requested amount, and maturity, the borrower also specifies her reservation interest rate. Through WebBank, Prosper acquired the borrower's credit reports. Without any evaluation, Prosper posted the loan and the borrower's credit attribute on its website for a 7-day open-bid multi-unit uniform-price auction with reservation price. lenders (bidders) specify the amount of funds to invest, and their interest rate bid on the investment. Lender's position are ranked in a descending order by their interest rate bids. Once the pledged amount exceeds the requested amount, the lowest winning interest rate is the ongoing interest rate for the loan. If the loan is not fully funded by expiration, the ongoing interest rate is the borrower's reservation price.

credit background, Prosper had granted 28,936 loans with 18,480 fully paid off and 10,456 loans defaulted, consisting of total loan volume of \$178K, \$47K of which was written off, implying a loss rate of 26.1%. On Oct.15, 2008, following LendingClub's return, Prosper exited the peer-to-peer lending market and began its process with SEC registration.<sup>37</sup> On

Figure 5: Return on Investments Prosper 2.0



Jul.13, 2009, Prosper announced its immediate return, began to set strict guidelines to borrowers and rename itself Prosper 2.0 (Compared to Prosper 1.0 before Oct.14, 2008).<sup>38</sup> Prosper 2.0 announced that it would only accept borrowers with FICO above 600 and started classifying borrowers into different risk ratings ranging from AA to HR by its evaluation of borrowers' creditworthiness, so that lenders can better understanding the default risk.<sup>39</sup> Similar to LendingClub, debt-consolidation is the main reason for loan request. Other purposes including home improvement and small business are also quite

<sup>37</sup>In early 2008, SEC requested both LendingClub and Prosper to be evaluated. LendingClub underwent its registration process on Apr. 8, 2008, and entered into a 'quiet' period, while it discontinued new lenders registration, took a halt in advertising to borrowers, and had funded many borrowers with own capitals. After roughly 6 months and on Oct.14, 2008, LendingClub announced its immediate return and all its loans issued henceforth can be traded on a secondary market. One day after, Prosper went quiet and commenced its registration. See <https://www.prosper.com/about-us/2008/10/15/prosper-filing-registration-statement-enters-quiet-period/>

<sup>38</sup>Prosper 2.0 is much improved compared to Prosper 1.0. (See figure 5, from A Look Back at Prosper 1.0 ? How Relevant are the Numbers? Lending Academy)

<sup>39</sup>'P2P lender Prosper is back and better than ever', AOL Finance

popular. (Figure 6)

Figure 6: Loan Purpose for Prosper 2.0, Left: application Right: issued

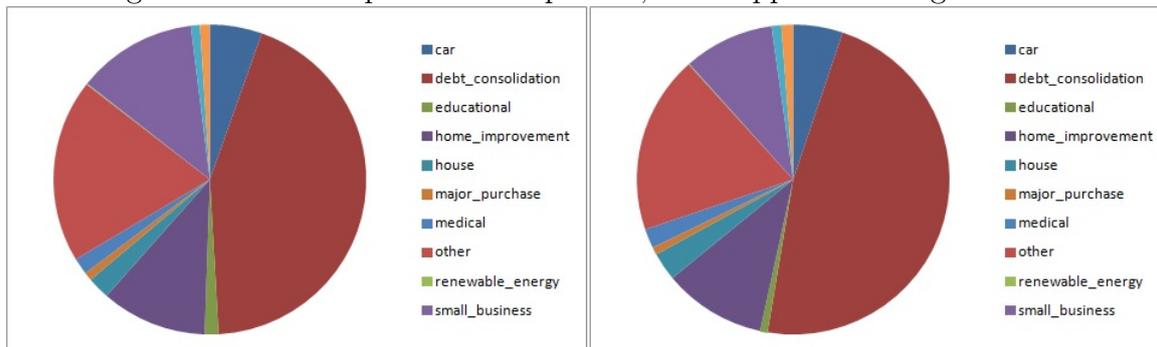


Table 3: Monthly Interest Rates and Origination Fees on Prosper in 2015

Loan Grade	AA	A	B	C	D	E	HR
Interest Rate	0.57%	0.77%	1.02%	1.36%	1.80%	2.22%	2.57%
Origination Fee	0.5%	4%	5%	5%	5%	5%	5%

At the time of its re-entry, Prosper and LendingClub were almost identical except several key discrepancies as follows. Foremost, still under the auction business model, lenders on Prosper placed bids on the interest rates, and thus did not observe the final interest rate until the loan was issued.<sup>40</sup> Both borrowers and lenders were and had always been price takers on LendingClub. Second, Prosper’s address information was at city level whereas LendingClub was at county level. Third, as aforementioned, the FICO scores on Prosper and LendingClub came from different agencies. More than what was observable on LendingClub, a lender can observe if the borrower was a repeated borrower on Prosper.<sup>41</sup> Regardless of the differences between them, preliminary results show that Prosper’s market re-entry tightens the competition with LendingClub.

<sup>40</sup>In Dec, 2010, Prosper got rid of the auction business model and switched to the posting-interest-rate business model as LendingClub, and the listing expiration for a loan increased from 7 days to 14 days. This event was studied by Wei and Lin (2016).

<sup>41</sup>Later on, LendingClub also added this feature.

### 2.2.3 Prosper 2.0 vs LendingClub

As aforementioned in the last paragraph, Table 4 shows the institutional differences between the two platforms. Table 5, shows the average interest rates for loans of different platform ratings issued from 2008-2010 on LendingClub and Prosper 2.0. Interest rates on Prosper were higher than LendingClub on average.<sup>42</sup> Figure 7 shows that no stochastic dominance on returns can be determined.

Table 4: LendingClub vs Prosper 2.0

	Interest Rate Pricing	Credit Report Agency	Borrower Guideline	Funded Borrowers	Repeated Borrower Observable
Prosper 2.0	Auction (Before Dec, 2010), then Platform Pricing	Experian	FICO>600	No	Yes
LendingClub	Platform Pricing	Transunion	FICO>640	Yes	No

Table 5: 2008-2010, Interest Rates Comparison

LendingClub	A	B	C	D	E	F	G
Interest Rate	0.006323	0.00919	0.011173	0.01263	0.013993	0.015469	0.017039
Prosper 2.0	AA	A	B	C	D	E	HR
Interest Rate	0.007169	0.009563	0.013892	0.017472	0.021682	0.026017	0.026901

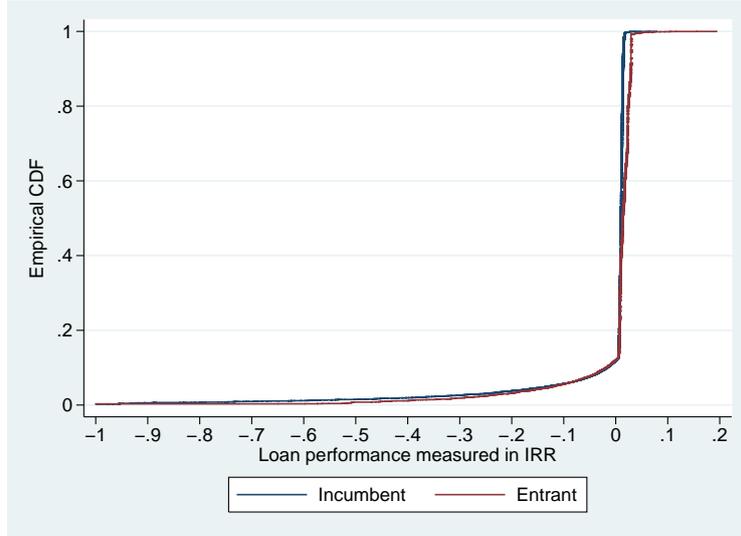
## 3 Data, Performance Measures and Statistics

### 3.1 Data on LendingClub and Macroeconomic Conditions

There are two pieces of unsecured loan data made available by LendingClub to the general public. One is a current snapshot of all the loans issued from 2007 to 2011 on LendingClub (loan issuance data) and the other is all the loans rejected in the same period (loan

<sup>42</sup>More comparisons are show when I discuss the market structure.

Figure 7: Cumulative Distributions of Loan Returns Between the Platforms



rejection data). There are two reasons that I do not extend the date after 2011. First, the event I study took place in 2009, two years before 2011. Second, loans can have maturity of 5 years, and thus some performance information is censored.<sup>43</sup> Both datasets are cross-sectional, and the observations are at loan level.

For loan issuance data, each observation represents an issued loan uniquely identified by loan id. I, as an econometrician, observe variables on 3 blocks of information, the loan contract, the borrower characteristics and the ex post loan performance.

A loan contract captures requested loan size by the borrower, the actual funded amount, separated into that by investors and by the platform, the loan term (36/60 month), the interest rate (from the funded amount and the interest rate, monthly installment/contractual payment schedule), its grade classified by LendingClub, loan origination date, and intended purpose of the loan.

For borrower characteristics, the information contains her basic attributes and her credit history. Her attributes are characterized by her address at a county-level (3-

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<sup>43</sup>I obtained the data in mid 2016

digit zip-code and state), her job title, the length of her employment, annual income, whether the stated income is verified, homeownership (rent, own or mortgage), her full description on the funding page. A borrower's credit history includes her FICO score range at the time of the application, her debt-to-income ratio (Excluding mortgages or the loan from LendingClub), number of credit lines, credit revolving balance and utilization, number of delinquency in the past two years, and when she opened her first credit line (in month/year).

A loan's performance is first pinned down by the status of the loan. In the data, it is either fully paid off or charged-off (defaulted). I observe the total payments on each loan, split into total payments towards the interest and the principal, and the last day of payments.<sup>44</sup>

Other measures such as number of lenders on each loan and loan application date are not observable in the data, but can be obtained on LendingClub's website for each loan's archived funding page. With 'loan id' as the identifier, I run a scraping script and parse the information on LendingClub's website, and merge these two additional features to the loan issuance data.

For the loans rejection data, each observation stands for a loan rejected by the platform. It has 7 variables, the application date, the requested loan size, its intended purpose, the borrower's FICO score, debt-to-income ratio, her zip-code and her employment length. I concatenate the two pieces (loan issuance and rejection) of data by the same measures and create a variable denoted by 'accept' to indicate if a loan is issued or rejected.<sup>45</sup>

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<sup>44</sup>Recoveries and collection fees are also recorded but of no interest in this paper, and thus, will not be mentioned.

<sup>45</sup>I let the FICO score be the lower bound of the FICO score, denoted by 'FICO range low'. Loan

I add several variable to control for the monthly macroeconomic environment: AAA bond yield, S&P return, mortgage rate, the spread between deposit rate and credit card interest rate (Freedman and Jin (2008)). Peer-to-peer lending market size heavily depends on the outside option for both lenders and borrowers.

### 3.1.1 Prosper Data

Since this paper focuses on how the entrant (Prosper 2.0) affects the incumbent (LendingClub), the data on Prosper isn't needed directly. Indirectly, data on Prosper provides a scope for me to identify the type of competition and thus is included in the analysis.

Prosper also made two pieces of data accessible to the general public on its website, loan listing data and loan performance data. For the same reasons as LendingClub, I only look at loans listed or originated before 2012. The loan listing data includes observations of both issued and dropped loans that once were listed on Prosper 2.0 (after July, 2009). Identified by a listing number, a loan listed can end up with 4 different status, 'Expired', 'Canceled', 'Withdraw' or 'Complete'.<sup>46</sup> A loan issued if and only if its status is 'Complete'. I merge the issued loan listing data with the performance data.<sup>47</sup>

Since the two platforms acquire similar information on the borrowers, the structures of their data are almost identical. Some major distinctions are as follows. Prosper does not lend to the borrowers, and thus all loans are funded by the lenders. In contrast to Lend-

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applications that were not funded to 70% or canceled by the borrowers are not observed in the datasets.

<sup>46</sup>For an 'Expired' listing, the funded amount does not reach a sufficient amount to issue (70%) by expiration date (7 days or 14 days after application). When Prosper changed its business model in Dec, 2010, it extended the listing period from 7 days to 14 days. A 'Canceled' listing means that the borrower's information is incomplete or cannot be verified. Withdraw indicates that the listing is dismissed by the borrower herself.

<sup>47</sup>The datasets do not have a common key to merge on. The loan performance data includes loan number as the identifier but does not contain listing number, and vice versa. Prosper API service provided by Prosper resolves the issue. Using the API, I could track down each 'Complete' listing's loan number and thus merged the two files.

ingClub, Prosper’s data indicates repeated borrowers.<sup>48</sup> Borrowers’ debt to income ratios include the current loan from Prosper.<sup>49</sup> Other minor differences include information on employment, address, and homeownership, etc.<sup>50</sup>

## 3.2 Performance Measures

A loan’s performance can be measured in relative to its contract or in its absolute return. I propose two relative measures, Default and Percentage Nonpayment and one absolute measure, Internal Rate of Return.

### 3.2.1 Default

Whether a loan defaults is a straightforward but coarse measure on loan performance. It does not provide any informativeness on the severity of default. For example, this measure equates a loan with zero return to another that is almost paid off. Hereby, I propose two additional measures.

### 3.2.2 Percentage Nonpayment

Percentage Nonpayment is defined as the ratio of the unpaid amount to the contractual payment:  $\text{Percentage Nonpayment} = \frac{\text{Contractual Payment} - \text{Actual Payment}}{\text{Contractual Payment}}$ , where ‘Contractual Payment’ is its monthly installment multiplies by the loan term. It measures how much a loan is short of the payments according to the contract. Since some loans are paid off early, its total payment may not coincide with the contractual pay-

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<sup>48</sup>Additional information includes borrowers’ previous loan performance.

<sup>49</sup>Remember, LendingClub excludes mortgages and LendingClub loan in the calculation.

<sup>50</sup>In addition to employment length and occupation, prosper informs lenders on borrowers’ employment type such as full-time/part-time. For borrowers’ addresses, Prosper uses city name in comparison to zip-codes by LendingClub.

ment.<sup>51</sup> Therefore, for loans that are fully paid, I let its 'Percentage Nonpayments' be 0. Nonetheless, this measure has a couple limitations. It ignores discounting since it doesn't take into account the timing of the payments. This measure can also create complexity. Some defaulted loans may have more accrued payments than its 'Contractual Payment' because of delinquencies, and thus, will result in negative Percentage Nonpayments.

### 3.2.3 Internal Rate of Return

The internal return (IRR) is the break even discount rate for investors. It is the discount rate so that the net present value (NPV) of the investment is 0.  $K = \sum_{t=1}^T \frac{P_t}{(1 + \text{IRR})^t}$ , where,  $K$  is the funded amount,  $P_t$  is the payment of the loan at time  $t$ , and  $T$  is the loan term, 36 or 60 months. I use IRR to measure both contractual interest rates and their ex post returns.

I compute the contractual IRR from the cash flow out (funded amount) and cash flows in (monthly installments), where  $T$  is the loan term. To compute the actual IRR, I make several assumptions. First, if a loan is paid off, regardless of possible delinquencies or early payments, its actual IRR is equal to its contractual IRR. Second, from what I observe, the total payments and the last payment date, I cannot infer the cash flows. I assume the payments are evenly distributed between the first month and the last one. Namely,  $P_t = \frac{\text{Total Payments}}{\text{Number of Payments}}$ . Lastly, if there is no payment ever made on a loan, I set its IRR to be  $-1$ .<sup>52</sup>

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<sup>51</sup>A typical reason for a loan gets prepaid is to avoid further interest payment. There is no additional fee for a loan to be prepaid.

<sup>52</sup>The actual IRR goes to  $-\infty$ .

### 3.3 Data Concatenation

To determine the type of competition, I pool the data together between LendingClub and Prosper. Without making any assumption, I concatenate variables of the same measure, for instance: income, loan origination and application date, interest rate (IRR), performance (loan status, nonpayment percentage ,IRR), funded and requested amount in dollars, loan purpose, employment length, address at state level, number of funders.

For differentiated measures such as FICO score, debt to income ratio, finer address at county level, I make additional adjustments and assumptions. Since I could not find a bijective mapping between the two FICO score system (Experian for Prosper and Transunion for LendingClub), I assume they are equivalent. Using the variable income, debt to income ratio and loan size of Prosper's data, I compute debt to income ratio excluding Prosper's loans. I run another python scraper that looks up the state and city names on 'www.zipinfo.com', and transform the addresses at city-level into county-level, or 3-digit zipcodes. With all the measures matched, I concatenate data from both platforms into a joined dataset.

## 4 Preliminary Results

### 4.1 Descriptive Statistics

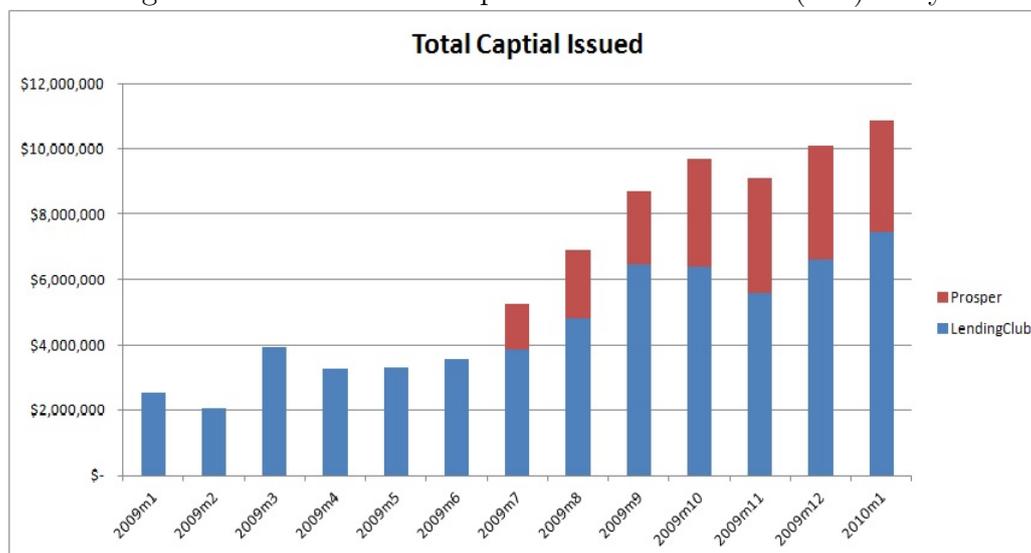
### 4.2 Entry and Competition

#### Market Structure Timeline



During the six months before Prosper’s re-entry, LendingClub has been monopolizing the market and issuing roughly \$4 millions of loans per month. The post entry joint issuance between the two platform reached around \$6 millions monthly, with a quarter of market share going to Prosper. (Figure 8)

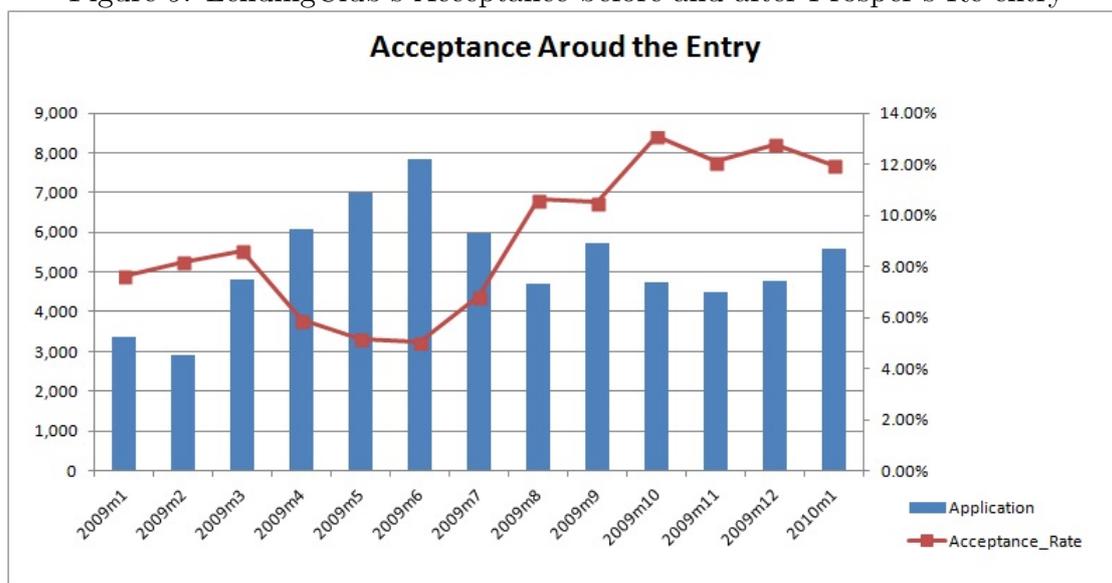
Figure 8: Total Market Capital Before and After (Re-)Entry



### 4.2.1 Entry and Borrower Acceptance

Figure 9 shows that after Prosper's entry, the number of application on LendingClub tumbled by around 2000. However, the average acceptance rate skyrocketed from 4% to 10%, and the average loan size jumped from \$7,000 to \$10,000 in two months, indicating possible incentive shifting on the incumbent.

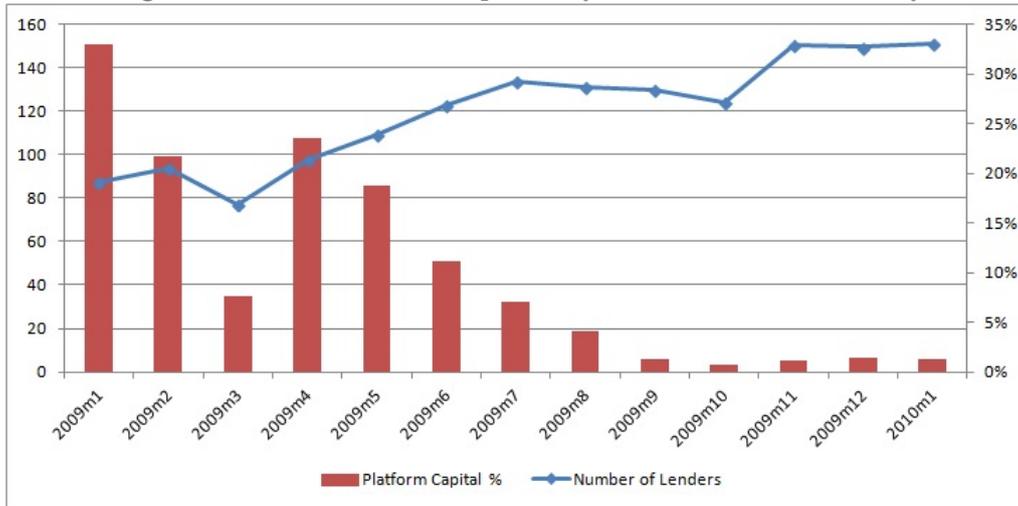
Figure 9: LendingClub's Acceptance before and after Prosper's Re-entry



### 4.2.2 Entry and Lender Participation on the Incumbent

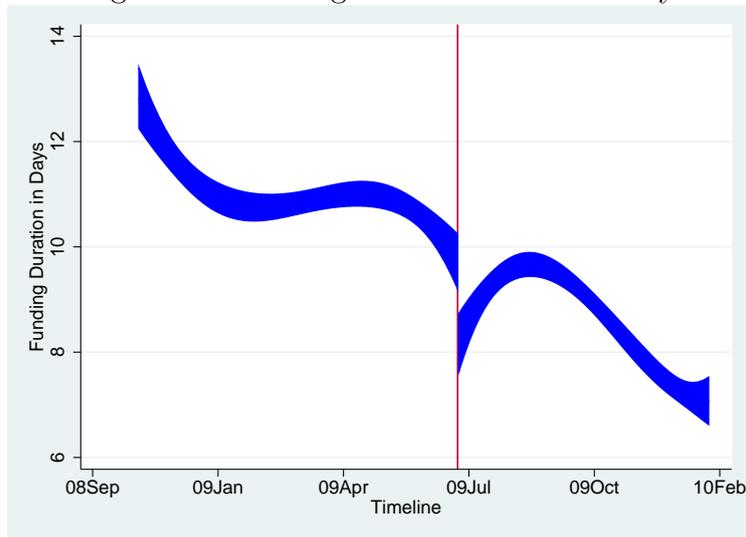
The growth of average number of lenders per loan was around 10 people per month before the entry. The growth disappeared right after the entry, indicating an emerging competition on new lenders due to the entry. In the meantime, the percentage of capital provided by the platform on an average loan kept decreasing around the entry. Remember, the average loan size increased from \$7,000 to \$10,000. This leads to two direct implications. First, average amount per lender increases. Second, loans are more likely to be filled by lenders. (See Figure 10) I define another measure, 'funding duration', as the time

Figure 10: Lenders and Capitals by Platform around Entry



between a borrower’s loan application and its origination date. Figure 11 illustrates local polynomial fits of ‘Funding Duration’ with discontinuity at the time of the entry. It dropped from well above 10 days prior to entry down to below 10, indicating loans are more easily to be filled and issued. Motivated by the preliminary results, in the following

Figure 11: Funding Duration around Entry

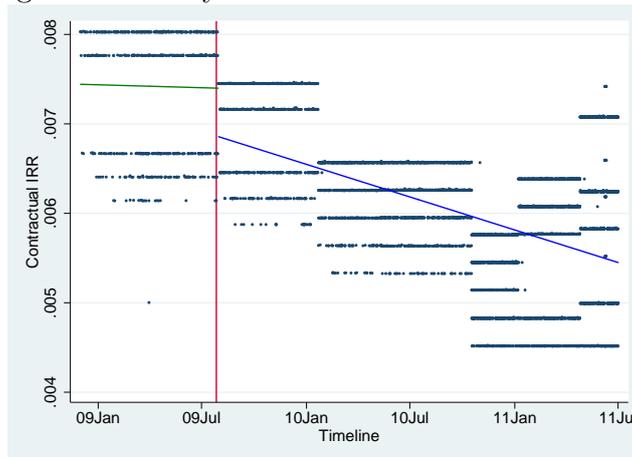


sections, I describe the data and elaborate on the empirical strategy.

### 4.2.3 Event Exogeneity

One may argue that Prosper's re-entry might be perceived by LendingClub before their official announcement. In this case, I need to verify the exogeneity of Prosper's re-entry. One direct way to test it is to see when the interest rate changed on LendingClub? Is it well before the entry or right at the time of entry? Figure 12 demonstrates the interest

Figure 12: Entry and Interest Rate for Grade 'A'



rate for Grade "A" loans from 2009-2011. The vertical red line indicates the time when Prosper entered the market, the same time when LendingClub lowered the interest rate for Grade A loans. This robust check verifies the exogeneity of the event to the incumbent.

## 5 Empirical Strategy

### 5.1 Hypotheses and Market Definition

The entry intensifies platform competition and affects the incumbent's incentives on borrower screening and loan pricing. I test three hypotheses. After entry,

- (i) the incumbent's incentive to screen borrowers mitigates, allowing more risky bor-

rowers to the market.

- (ii) controlling for borrower and loan characteristics, a borrower is more likely to receive better loan classification.
- (iii) interest rates decrease due to competition.
- (iv) loan performance on the incumbent is aggravated.

To test the hypotheses, I propose several empirical strategies on both loan screening, pricing and performance. Borrower  $i$  with characteristics,  $\{X_i, \mu_i\}$ , applies for a loan with size  $K_i$  and term  $T_i$  with a purpose of  $M_i$ , where  $K_i, T_i, M_i, X_i$  are observable to both econometricians and the platform, and  $\mu_i$  is some latent variable that is only observable to the borrower.<sup>53</sup> I assume the platform first observes a subset of  $X_i$ , denoted by  $Y_i$ , and makes its first decision. It decides whether or not to accept the borrower,  $\mathbb{1}_{\{\text{Accept}\}}$ . Second, if she is accepted, the platform gets to observe  $X_i$ , and chooses the interest rate  $I_i$  (or grade  $G_i$ ).<sup>54</sup>

In order to eliminate other possible exogenous changes that I am not aware of or able to control for, I look at a 1-year window around the time of the entry.<sup>55</sup> That gives me 6-month data on loans rejected and issued prior to and after the entry.<sup>56</sup> To control for characteristics of the population, I implement specifications including using macroeconomic controls and fixed effects, both of which requires definition of a market. Loan application date is at day-level, and to allow enough variation and power in the statistics, I define a market as all the loan applications submitted in a calendar month across U.S.

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<sup>53</sup>Note that if the platform does not own private information,  $\mu_i$  is an empty set.

<sup>54</sup>Remember, grade and interest rate is bijective at any point of time.

<sup>55</sup>An exogenous change can affect the distribution of the applicant pool, which reduces robustness/power of the hypothesis testing.

<sup>56</sup>Need robustness check.

I also allow variations across addresses, but I assume those are fixed overtime.<sup>57</sup> For borrowers' address, I choose the state-level instead of 3-digit zipcode for statistical power. In the macroeconomic control specification, to take into account the population changes, I include the first 3 moments for each quantitative variable in each market and a variable to denote the number of applications.<sup>58</sup>

## 5.2 Borrower Screening

Whether a borrower is accepted is a binary choice. If the preliminary signal,  $Y_i$ , is good enough (above some latent cutoff,  $\underline{x}$ , chosen by the platform), she will be accepted. First, I assume  $\mu_i + X_i|Y_i$  follows i.i.d. Normal distribution, and thus it becomes a probit model:<sup>59</sup>

$$\mathbb{E}\{\mathbb{1}_{\{\text{Accept}\}}|Y_i\} = \Phi(Y_i\beta) \quad (1)$$

Remember  $Y$  only includes features such as the borrowers' lowest FICO score, employment lengths, debt to income ratios, requested loan sizes, loan purpose, application date, zip-code and market fixed effects or market controls.

### 5.2.1 Entry and Loan Screening

To test the hypotheses, I define a variable named 'Entry' to indicate if a loan is applied before or after Prosper's entry. One reduced form way to test the hypothesis is to directly

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<sup>57</sup>In other words, I do not interact address with time.

<sup>58</sup>I compute the median, second moment and skewness for FICO score, debt to income ratio and requested loan size. I use median instead of mean to better characterize the population distribution due to outlier issues.

<sup>59</sup>Presumably it follows standard normal distribution due to identification restrictions.

include  $\mathbb{1}_{\{\text{Entry}\}}$  in the Probit model.

$$\mathbb{E}\{\mathbb{1}_{\{\text{Accept}\}}|Y_i\} = \Phi(Y_i\beta + \gamma_1 \mathbb{1}_{\{\text{Entry}\}}) \quad (2)$$

This model specification forces  $\beta$  unchanged across the entry, and  $\gamma_1$  measures the change in the cutoff  $\underline{x}$ . By the first hypothesis,  $\gamma_1 \gg 0$ . That is, after the entry, given the borrower with the same characteristics, she will be more likely accepted. From Table 8 column 1, I observe that controlling for all the observables. Entry induces the incumbent to accept more borrowers.

### 5.2.2 RDD

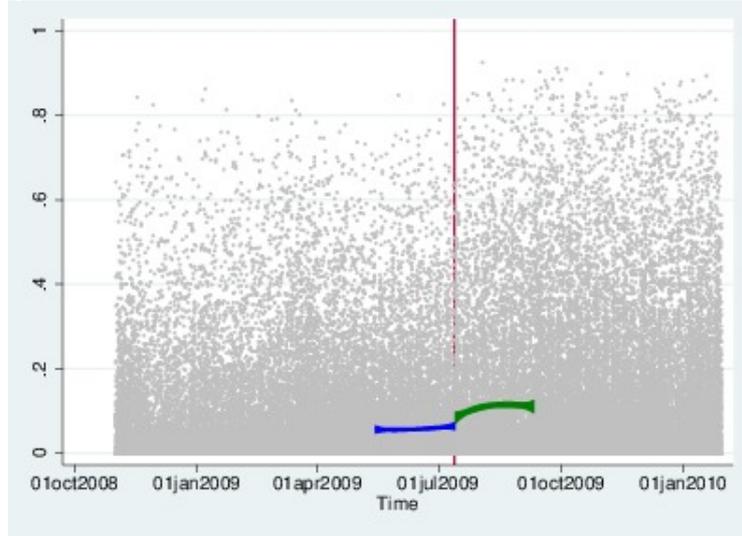
In comparison, to relax the assumption on constant  $\beta$  before and after Prosper's entry, I use regression discontinuity design (RDD) to estimate the change in the likelihood after entry. Specifically, I estimate the model separately for before and after the entry.

$$\mathbb{E}\{\mathbb{1}_{\{\text{Accept}\}}|Y_i, \text{Entry} = 1\} = \Phi(Y_i\beta_B|\text{Entry} = 1) \quad (3)$$

$$\mathbb{E}\{\mathbb{1}_{\{\text{Accept}\}}|Y_i, \text{Entry} = 0\} = \Phi(Y_i\beta_A|\text{Entry} = 0) \quad (4)$$

According to the models, I predict the propensity of acceptance for each applicant, and fit a local polynomial of degree 3 at a 2-month window, separately for the before and after entry periods. (See Figure 13)

Figure 13: RDD with Confidence Interval: Loan Selection



### 5.2.3 Discussion

## 5.3 Loan Classification and Pricing

Conditional on that borrower  $i$  is accepted, the platform obtains the full set of information  $X_i$  to classify (and price) the loan. Classifying a borrower into a bin is equivalent as assigning the loan with an interest rate since they are bijective.

### 5.3.1 Loan Classification and Selection Bias

I assume through an aggregation matrix, denoted by  $\theta$ , a borrower's signals  $X_i$  will be mapped to a one dimensional signal  $X_i\theta$ . Depending on the value of  $X_i\theta$ , the loan will be associated with a grade. Since grades are ordered ascending from A to G, I propose an Ordered Probit model to estimate  $\theta$ .<sup>60</sup> The underlying assumption for this model is that it allows multiple latent cutoffs (vs. one cutoff for a binary choice model). Borrower  $i$  still has unobservable characteristics. However, its distribution changed since the first

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<sup>60</sup>Order Probit(Logit) models are conventional in credit rating estimations.

stage selection censors unqualified borrower, i.e.  $\mu_i^* = \mu_i | (\mathbb{1}_{\{\text{Accept}\}} = 1)$

$$\text{Grade} = \begin{cases} A & \underline{x}_A \geq X\theta + \mu_i^* \\ B & \underline{x}_B \geq X\theta + \mu_i^* > \underline{x}_A \\ C & \underline{x}_C \geq X\theta + \mu_i^* > \underline{x}_B \\ D & \underline{x}_D \geq X\theta + \mu_i^* > \underline{x}_C \\ E & \underline{x}_E \geq X\theta + \mu_i^* > \underline{x}_D \\ F & \underline{x}_F \geq X\theta + \mu_i^* > \underline{x}_E \\ G & X\theta + \mu_i^* > \underline{x}_F \end{cases} \quad (5)$$

where  $\mu_i^*$  longer follows normal. I use Heckman two-stage to correct for selection bias.<sup>61</sup>

The second hypothesis states that borrowers are more likely to receive better classifications. I conduct pairwise t-tests between the estimated cutoffs before and after the entry. (Table 6)

Table 6: Estimated Cutoffs Comparison

	Pre-entry	SE	Post-entry	SE	Pre - Post	t-score
$\underline{x}_A$	-73.51	2.55	-63.89	2.97	-9.62	2.46
$\underline{x}_B$	-70.51	2.50	-60.02	2.92	-10.50	2.73
$\underline{x}_C$	-67.74	2.45	-57.38	2.89	-10.36	2.73
$\underline{x}_D$	-65.59	2.42	-54.98	2.88	-10.61	2.82
$\underline{x}_E$	-63.77	2.40	-52.98	2.87	-10.79	2.88
$\underline{x}_F$	-62.57	2.41	-51.08	2.88	-11.48	3.06

### 5.3.2 Discussion

### 5.3.3 Loan Pricing

How does entry affect the incumbent's loan pricing? A quick way to observe it to plot loan interest rate within each loan grade. Using a discontinuity design at the time of the

<sup>61</sup>One can also use maximum likelihood method.

entry, I fit a linear trend on the interest rate over time for each grade. Figure 14 shows the interest rate for grade A measured by IRR over time, and Figure 15 for grade G, the most risky borrowers. Figure 14 coincides with our hypothesis where competition lowers

Figure 14: Entry and Interest Rate for Grade A

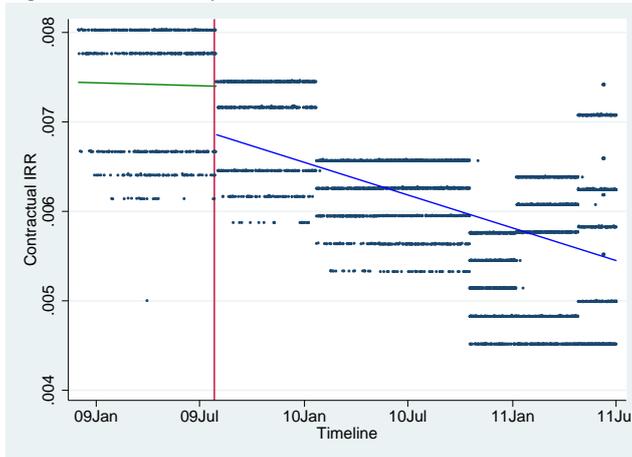
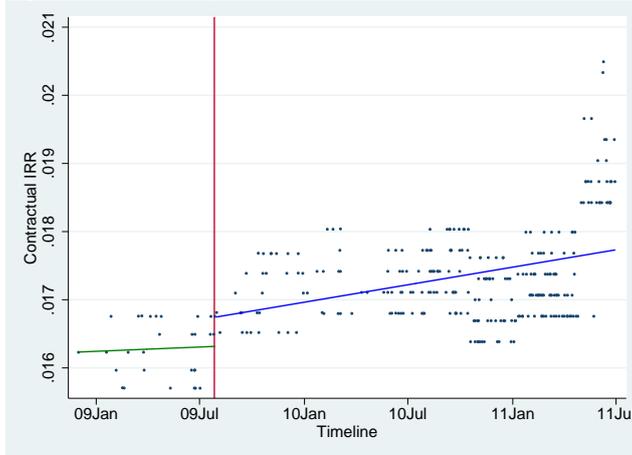


Figure 15: Entry and Interest Rate for Grade G



the interest rate. Nonetheless, Figure 15 contradicts to that.

To better analyze the magnitude with in each classifications, I interact "Entry" dummy with loan classification in a linear model. Note that there are 35 grades with 35 interest rates at any snapshot of time. I use a coarser measure on loan classification A,B,C,...,G.

$$IRR_i = \gamma_2 \text{Grade}_i \times \mathbb{1}_{\{\text{Entry}\}} + \varepsilon \quad (6)$$

where  $\gamma_2$  (a vector) measures the average treatment effect. See Table 8 column 3.

## 5.4 discussion

Competition on borrowers itself cannot explain the heterogeneity of the pricing change direction. Several additional factors can explain this phenomenon.

First, it maybe due to adverse selection induced by competition. Since the information between the two platforms are differentiated, a 'lemon' to one platform can be a 'qualified' borrower to the other. The winner's curse provides incentive for platform to not undercut. Second, more than the borrowers' side, the platforms also compete for the lenders. Is raising the interest rate on risky loans simply to target more lenders? I test the possible factors as follows.

### 5.4.1 Adverse Selection

A straightforward way to test adverse selection is to bilaterally match between rejected/unfunded borrowers from one platform to accepted/funded borrower from the other. Since I do not access borrowers' identities such as social security number or name, I use several measures shared by both platforms that I argue do not vary within the a market, including loan application date, address, opening date of a borrower's first credit line, income and employment length.<sup>62</sup>

I look for a fuzzy bilateral match between an funded borrower from the entrant and an funded one from the incumbent. I use data from both platforms with a time window of 6 months after Prosper's entry. Within the same market, I identify 38 individuals

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<sup>62</sup>I weigh in the fact that income and employment length can be unverified.

appearing on the two platforms with identical zipcode and first credit line date.<sup>63</sup> Keeping the reported income difference between the platforms below \$20K, I end up having 20 matches in the 6-month duration, which is incomparable to thousands of loans issued.

#### 5.4.2 Competing for Lenders

In contrast to borrowers, given the same risk between two borrowers, lenders prefer the higher interest rate. As previously shown, loans have unconditional average higher interest rate on Prosper, the entrant, which may provide incentives for the incumbent to raise interest rate. I test this hypothesis from two different angles.

First, I use the concatenated dataset with a 6-month post-entry time window to compare their interest rates conditional on borrower and loan characteristics, and further their loan performances. I propose a linear model on the interest rate pricing. To avoid possible non-linear functional form, I estimate the semi-elasticity. The coefficient  $\delta$  captures the average pricing premium or discount from the entrant:

$$\log(\text{IRR}_i) = \alpha + X_i\theta + \delta\mathbb{1}_{\{\text{Entrant}\}} + \mu_i$$

To reduce the heavy selection bias, I only look at only borrowers whose characteristics overlap.<sup>64</sup> Table 9 shows that compare to the incumbent, the interest rate on the entrant is 28% higher, indicating a possible reason why the incumbent has incentive to raise the interest rate.

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<sup>63</sup>By definition of a market, the difference between the application dates is less than 30 days.

<sup>64</sup>I define an overlapping borrower as follow. With in the same market, borrower i on the incumbent has characteristics  $x_i = (x_{1,i}, x_{2,i}, \dots, x_{n,i})$ . She is overlapping with the entrant if and only if every quantitative component of  $x_i$  is bounded between the minimum and the maximum of the same variable of the entrant. Similarly, I identify borrowers from the entrant who overlap with the incumbent.

Second, to directly observe how changes in the interest rates affect lenders' incentive, I compare number of lenders per loan on the incumbent before and after the entry. Figure 16 shows that as the interest rates change divergently, the number of funders diverge in the opposite direction. With higher interest rates, risky loans attract more borrowers.

From a different perspective, how do the interest rate changes affect the capital provision by incumbent platform as a lender? Figure 17 shows the trend of capital provision by the platform measured in percentage of the loan size. Separated by creditworthiness, 'Grade' A loans do decline as sharp as 'Grade' G. I contend that the sharp rise of demand for risky loans is due to a higher interest rate.

Figure 16: Entry and Number of Funders: Left, Grade A | Right, Grade E,F& G

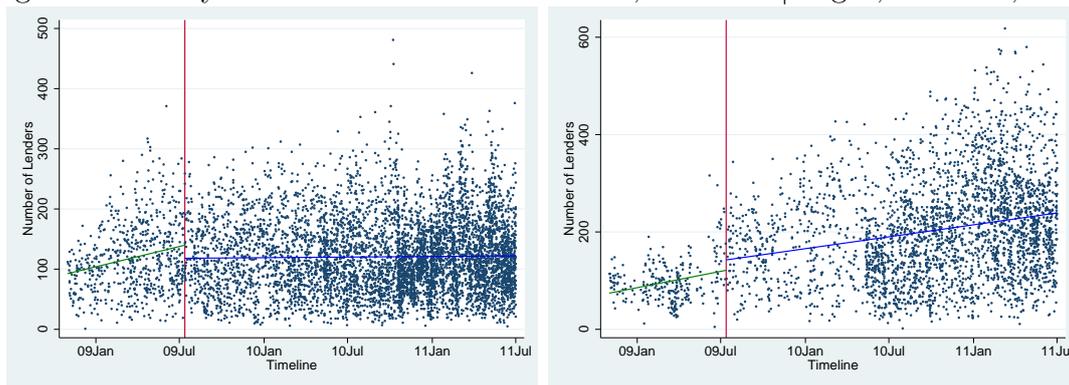
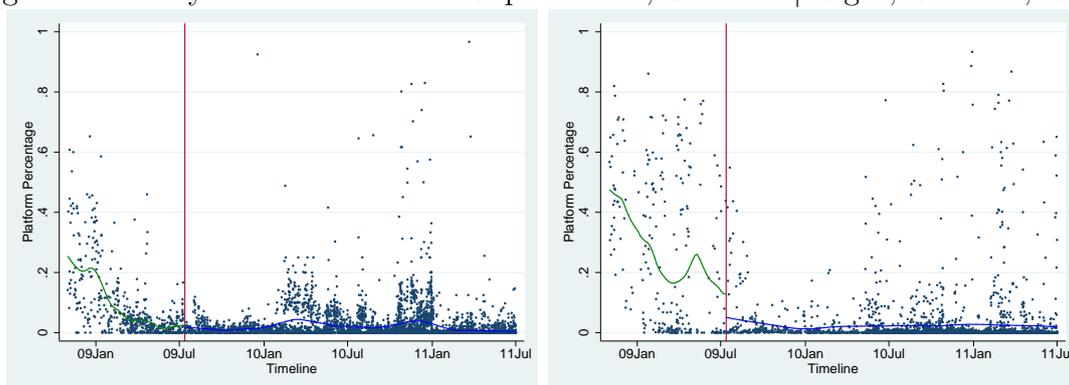


Figure 17: Entry and Pct Platform Capital: Left, Grade A | Right, Grade E,F& G



## 5.5 Entry and Loan Performance

After failing to reject the hypotheses that the incumbent platform accepts more risky borrowers and assigns them with better ratings, how does it affect the ex post loan performance. Using all three measures, default rate, nonpayment percentage and internal rate of return, I verify the third hypothesis.

### 5.5.1 Default

Default is a straightforward measure but as aforementioned, it is not informative.<sup>65</sup>

(As borrowers only pay up to the interest rate, one cannot observe the actual return of their projects. If the accepted borrowers before and after the entry are drawn from the same distribution, a decrease in interest rate would result in less default, and vice versa.)

I assume for borrower  $i$ , with characteristics  $X_i$ , takes a loan with interest rate  $I_i$  (measured in IRR). Default her loan is defined as her return  $R_i$  is below the interest rate  $I_i$ ,  $\mathbb{1}_{\text{Default}} = \mathbb{1}_{R_i < I_i}$ . Similarly, I use a probit approach to maximize the likelihood of the data:

$$\mathbb{E}\{\mathbb{1}_{\{\text{Default}\}}|X_i\} = \Phi(X_i \cdot \lambda) \quad (7)$$

To test how entry affects loan performance, I use  $\mathbb{1}_{\{\text{Entry}\}}$  to measure the change in the likelihood of a default. That is:

$$\mathbb{E}\{\mathbb{1}_{\{\text{Default}\}}|X_i\} = \Phi(X_i \cdot \lambda + \gamma_3 \mathbb{1}_{\{\text{Entry}\}}) \quad (8)$$

---

<sup>65</sup>Note that "Default" here isn't equivalent to a default in corporate finance literature. A loan is partially paid off are still marked as default, but it has a different return from those that are not paid at all.

The coefficient of interest is  $\gamma_3$ , and I expect  $\gamma_3 \gg 0$ . Table 11 supports the evidence that the default rate increases with competition.

### 5.5.2 Overall Performance by IRR

Despite the interest rate change, I estimate how the entry affect the overall performance and performance within each classification. I run the following regressions:

$$\mathbb{E}\{IRR|X\} = X\beta + \gamma_4 \mathbb{1}_{\{\text{Entry}\}} \quad (9)$$

$$\mathbb{E}\{IRR|X\} = X\beta + \gamma'_4 \mathbb{1}_{\{\text{Entry}\}} \times \text{Loan Grade} \quad (10)$$

The coefficients of interest is  $\gamma_4$  and  $\gamma'_4$ . Table 11 further proved my hypothesis that the overall loan performance deteriorated due to competition. However, we cannot distinguish performance deterioration from interest rate change. A lower interest rate can result in average lower performance. However, separated by loan grade, Table 12 shows the performance varied by loan classification. Even with a higher interest rate, loan performance deteriorates the most within grade D and E.

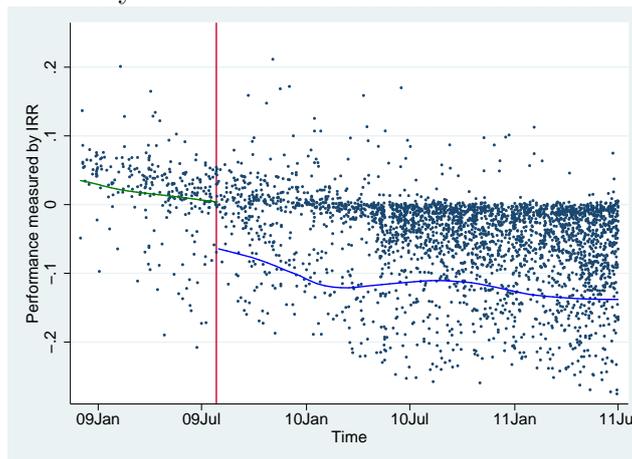
### 5.5.3 Subsamples, RDD and Heckman Correction

By the assumption that a loan is charged off when the return on the project cannot pay it off. We only observe the actual return  $Z_i$  if the project is defaulted, i.e.  $\mathbb{1}_{\text{Default}} = \mathbb{1}_{Z_i < I_i}$ . I measure  $Z_i$  using the actual internal rate of return calculated on each loan. Given the characteristics:

$$\mathbb{E}\{IRR|X_i, \mathbb{1}_{\text{Default}}\} = X_i\beta | \mathbb{1}_{\text{Default}} \quad (11)$$

I measure the change in project returns by implementing a regression discontinuity design.<sup>66</sup> I first estimate the equation above restrict in the sample where Entry=0 and Default=1. Then, I estimate the same equation for those where Entry=1 and Default=1. I predict and compare the fitted values. Note that we also control for the interest rate and the macroeconomic environment or the fixed effects at the time of the default for each loan.<sup>67</sup> Figure 18 shows the polynomial fit of performance measured by IRR over time, at the discontinuity at the time of the entry, controlled for monthly fixed effect at the time of default for each loan. Table 10 examine the difference in the loan performance prior and after the entry with their propensity score matched.

Figure 18: Entry and Performance over Defaulted Population



In the next section, I propose a static model to explain the connection between bank competition and loan performance.

## 6 Appendix

### 6.1 Descriptive Tables and Estimation Results

<sup>66</sup>Other methods such as propensity score matching can also demonstrate the result

<sup>67</sup>The time of the default is assumed to be the last payment date on a loan.

Figure 19: Prosper 2.0: IRR for Loans Vintaged from 2009-2010

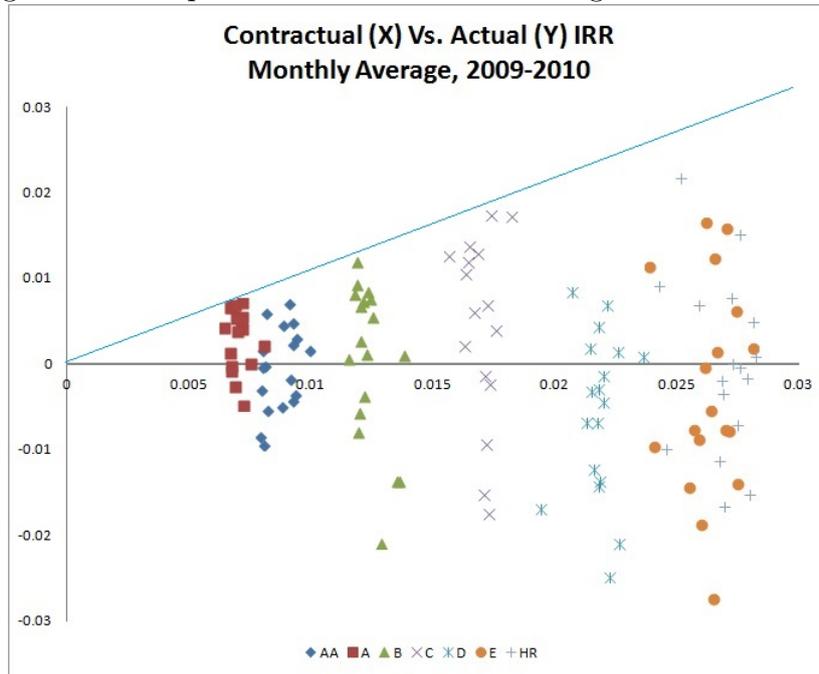


Table 7: Investment Before and After the Entry

Date	Mean(Investors)	Sd(Investor)	Mean(Investment)	Sd(Investment)
2009m1	87.58	41.08	6030.95	3088.14
2009m2	93.83	47.51	6246.40	3406.48
2009m3	77.14	47.08	8411.57	4617.92
2009m4	97.81	56.46	6117.07	3463.34
2009m5	109.30	60.02	6614.41	3631.93
2009m6	123.03	59.61	7310.30	4097.97
2009m7	133.75	61.02	8343.60	4395.08
2009m8	131.38	67.04	9094.19	5155.95
2009m9	129.74	63.83	10602.45	6081.95
2009m10	123.86	63.99	10238.30	6483.34
2009m11	150.67	77.62	10053.49	6216.13
2009m12	149.59	81.54	10722.28	6819.21
2010m1	150.91	76.70	11018.30	6428.73

Table 8: Entry and Borrower Screening and Loan Pricing

	<i>Selection: <math>\mathbb{1}\{\text{accept}\}</math></i>	<i>Int_rate (in %)</i>	<i>Int_rate <math>\times</math> loan_class</i>
Entry	0.1363*** (6.67)	.0089* (1.93)	
FICO	0.0114*** (132.28)	-0.0064*** (-200.33)	-0.007*** (-35.03)
DTI	-2.4660*** (-69.32)	-0.2737*** (15.98)	-0.0171*** (-2.78)
Loan Size(\$1K)	-0.0309*** (-56.65)	0.0164*** (83.97)	0.0021*** (27.36)
Borrower Income (1K)		-0.0001*** (-2.77)	-0.0001*** (-3.81)
Grade Dummies			(Suppressed)
Grade A $\times$ Entry			-0.1148*** (-34.74)
Grade B $\times$ Entry			-0.0411*** (-15.81)
Grade C $\times$ Entry			0.0580*** (24.49)
Grade D $\times$ Entry			0.0996*** (34.46)
Grade E $\times$ Entry			0.1177*** (29.90)
Grade F $\times$ Entry			0.1377*** (20.76)
Grade G $\times$ Entry			0.1216*** (13.76)
Observations	270,846	26,900	26,900
R <sup>2</sup>		0.95	0.95

*All SEs are Robust*

\*p&lt;0.1; \*\*p&lt;0.05; \*\*\*p&lt;0.01 || z/t score in parentheses

Macroeconomic Controls: S&amp;P, Mortgage rate, AAA yield

Table 9: Dependent Variable: log(Interest Rate)

Variable	Coefficient (Std. Err.)
l(Entrant)	0.283*** (20.11)
Loan Size	0.015*** (25.38)
Debt to Income	0.115* (1.88)
FICO	-0.006*** (-49.66)
Revolving Utilization	0.062*** (3.66)
N	
	4138
R <sup>2</sup>	
	0.560

Suppressed variables: loan purpose, income, employment length, monthly FE, etc.

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

Table 10: Propensity Score Matching for Defaulted Loans

Variable	Coefficient	(Z.Score)
IRR (Post-Entry vs. Pre-Entry)	-11.216	(-8.94)

Table 11: Entry and Loan Performance

	<i>with Time FE:</i>	
	Default (Probit)	IRR (in %)
Entry	0.6227*** (14.56)	-5.39*** (-24.93)
Funded Amount	.0033 (1.34)	0.0281** (2.08)
FICO	-0.0071*** (-21.35)	0.0129*** (8.70)
DTI	0.5427*** (3.19)	-3.64*** (-4.36)
Number of Funders (1K)	0.9591*** (5.46)	-0.0022*** (-2.72)
Funding Duration	.02181*** (7.08)	-0.1014*** (-6.47)
Observations	26,531	26,531
<i>Other FE: purpose, homeownership, state</i>	*p<0.1; **p<0.05; ***p<0.01	

Table 12: Performance Change across Loan Grades

Loan Grade	Default, $\gamma_3$	$ z $	Return, $\gamma_4$ (%)	$ t $
A	0.234	1.88	-1.13	4.38
B	0.382	3.48	-1.96	6.20
C	0.389	3.70	-1.95	5.44
D	0.311	2.50	-2.38	5.07
E	0.388	1.99	-2.77	3.63
F	0.109	0.36	-1.15	0.74
G	-0.332	0.78	0.36	0.34

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