Platform Mispricing and Lender Learning in Peer-to-Peer Lending*

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Abstract

We document how online lenders exploit a flawed, new pricing mechanism in a peer-to-peer lending platform: Prosper.com. Switching from auctions to a posted-price mechanism in December 2010, Prosper assigned loan listings with different estimated loss rates into seven distinctive rating grades and adopted a single price for all listings with the same rating grade. We show that lenders adjusted their investment portfolios towards listings at the low end of the risk spectrum of each Prosper rating grade. We find heterogeneity in the speed of adjustment by lender experience, investment size, and diversification strategies. It took about 16 – 17 months for an average lender to take full advantage of the "cherry-picking" opportunity under the single-price regime, which is roughly when Prosper switched to a more flexible pricing mechanism.

Keywords: firm learning, pricing mechanisms, peer-to-peer lending

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1 Introduction

Economists analyze demand and supply at market equilibrium; they often neglect the time that is needed to reach the equilibrium in a changing marketplace. How do market participants respond to policy changes? How long does it take to reach a new steady state? During the adjustment process, who wins and who loses? How do these tradeoffs affect market evolution? Answers to these questions are crucial for the improved design of market mechanisms when it is time for a change. When a market mechanism fails to consider the strategic reactions of market participants, a small mishap may have large adverse consequences.

In this paper we provide a case study of Prosper.com: the earliest and second-largest peer-to-peer lending platform in the U.S. (by loan volume to date). Prosper originated in 2006 with an auction mechanism in which a borrower states the maximum interest rates she is willing to accept for a loan request and a lender bids a minimum interest rate he is willing to accept and a loan amount at this interest rate.[1]

On December 20, 2010, Prosper unexpectedly switched to a posted-price mechanism in which the platform specified the interest rates for all loan listings. Based on borrower credit information from consumer credit reports and past borrower repayment history on the platform, Prosper calculated an estimated loss rate for all loan listings. Prosper then categorized all loan listings into seven credit grades: AA, A, B, $\cdots$, E, HR (high risk); each rating grade corresponded to a range of estimated loss rates. These seven grades were called Prosper ratings, and Prosper simply assigned a single interest rate for all loan listings that carried the same rating grade.[2] The coarse interest rate categorization makes it apparent that loan listings with relatively low inherent risk within each Prosper rating are preferable to their higher-risk counterparts within the same rating grade.

Did Prosper participants—online lenders and borrowers—immediately react to this "cherry-picking" opportunity that had been created by Prosper? If not, how long did it take for them for learn and adjust? To address these questions, we construct a panel of all Prosper lenders'

[1]In contrast, Prosper's main competitor and the largest peer-to-peer lending platform in the U.S. – Lending Club – adopted a posted-price pricing policy from day one and has since kept this pricing policy.

[2]Lending Club categorizes its loan listings into 7 credit grades (A through G) and further classifies loan listings within each category into five (1 – 5) subcategories, thus leading to $7 \times 5 = 35$ (A1 – G5) different interest rates.

monthly investment portfolios from December 2010 to February 2013, which covers the entire period when Prosper operated under this single-price regime and a short period after Prosper changed the pricing mechanism again. We first show that lenders adjusted their investment portfolios towards listings at the low end of the risk spectrum of each Prosper rating grade. We then use panel-data regression methods to investigate how lenders' investment portfolios evolved over time. We find that lenders steadily increased their holdings of preferable loans over time and that the speed of adjustment slows down gradually. It takes about 16 – 17 months for an average lender to take full advantage of the opportunity under the coarse single-price regime, which is roughly when Prosper seemed to realize their mispricing problem and switched to a much finer pricing grid in July 2012. Our results also point to heterogeneity in learning ability among lenders: Larger lenders and lenders with a more focused portfolio took the "cherry-picking" opportunities immediately and slowly adjust downward later. In contrast, lenders with more experience on the platform adjust their portfolio toward plus loans with the passage of time.

A pricing mechanism plays a crucial role in the efficiency and proper functioning of online platforms. Many platforms make adjustments in their pricing mechanisms to cater to an everchanging marketplace.[3] The performance of a pricing mechanism depends critically on how well market participants understand the mechanism and on their ability to learn and adapt to the mechanism. A well-designed mechanism would incorporate how market participants adapt to the mechanism. If a flawed pricing mechanism is in place, participants would learn to take advantage of pricing opportunities, which might lead to severe adverse consequences for the marketplace. Although it lasted only 19 months, Prosper's flawed pricing policy has created distortions in the market place. As will be shown in Section 4.3, even loan listings that were relatively safe may not have been funded because they are located at the risky end of the spectrum covered by their Prosper rating. If the single-price regime had continued, the safer borrowers within each grade would have been driven out of the platform and the exodus of safe borrowers would take lenders away with them. A lack

[3]For example, eBay has tried simple auctions, auctions with buy-it-now (BIN) options, and pure posted prices in various time periods. Figure 1 in Einav et al. (2018) shows the relative popularity of auctions versus posted prices on eBay over time.

of variation in prices hampers the most fundamental function of prices to cause demand to meet supply, which may lead to the decline and even the shutdown of a marketplace.

This Prosper mispricing episode points out the possibilities that firms – including both online lenders and the lending platform in this case – can make mistakes and gradually learn to fix their mistakes. Online sellers did not immediately realize the opportunity for higher profit due to Prosper's mispricing; Prosper did not anticipate that their coarse pricing regime would lead to strategic responses of online sellers.

In essence, firms can be "behavioral": They do not always make fully rational decisions from a black box, in which they seek to maximize the present value of current and future earnings, anticipate uncertain market conditions and strategic rival actions, solve a dynamic optimization problem, and play a Bayesian Nash Equilibrium. Firms can be prone to behavioral biases, mistakes, and a limited ability to acquire and process information. In this sense, our work provides input to a nascent field — behavioral industrial organization — the intersection between behavioral economics and industrial organization (Camerer and Malmendier, 2007; Goldfarb et al., 2012).

Our work builds on a growing empirical literature on firm learning.[4] Micro, macro, and experimental economists have done extensive research on the theory of learning and which theory best fits how economic agents learn in the real world; however, empirical work is relatively sparse.[5] No consensus has been reached as to the appropriate learning model; but economists agree that it takes a nontrivial amount of time for competing agents to learn and adjust, and that this learning/adjustment mechanism may be critical in determining at which point the marketplace will finally rest. Most notably, Schmalensee et al. (1998) find that emissions rights markets – which were created by the 1990 Clean Air Act Amendments – have stabilized to a high degree of efficiency within four years of opening. Goldfarb and Xiao

[4]Firm learning is the other side of the coin that relates to the consumer learning literature. DellaVigna (2009) provides a comprehensive survey of behavioral anomalies on both the consumer and the firm sides. Ching (2010) investigates consumer learning under a similar situation as ours where the market conditions experienced a sudden change (patent expiration in his case).

[5]Aguirregabiria and Jeon (2019) provide a comprehensive review about how firms learn about demand, costs, or the strategic behavior of other firms in the market. In particular, Hitsch (2006) investigates firms' dynamic product launch and exit decisions with demand uncertainty. Jeon (2017) estimates firms' investment decisions with firm learning and demand shocks. Huang et al. (2018) study how firms set prices by learning product demand over time.

(2011) show that potential entrants into local telephone markets evolved to a much higher level of strategic sophistication five years after the 1996 Telecommunications Act opened the doorway to competitive entry. Doraszelski et al. (2018) find that it took more than three years for prices to converge to a resting point that is consistent with equilibrium play after the deregulation of the frequency response market in the UK electricity system. All markets in the above studies are complex, high-stake offline marketplaces. Our study suggests a shorter learning cycle of roughly one and a half years for online lenders to stabilize their portfolios when the platform changes its pricing rule completely. Again, we show convergence to steady state is not swift at all after a disruption in the marketplace. Moreover, we show that players have heterogeneous learning and adjustment ability as Conley and Udry (2010) point out, and this heterogeneity often determines the winners and losers in a constantly changing market.

Our work is particularly related to two studies on lender learning that use data from the same platform: Freedman and Jin (2018) find evidence of learning-by-doing as lenders learn about loan qualities from the performances of their previous investment portfolio. Zhang and Liu (2012) find that lenders engage in active observational learning by herding into well-funded loan listings: Lenders infer the riskiness of borrowers by observing and learning from peer lending behaviors. Our study provides further evidence as to learning dynamics and the heterogeneity of online lenders: In our study lenders learn how best to respond to a new pricing rule, rather than to the riskiness of loan listings.

Our study also adds to the flourishing literature on crowdfunding and other online platforms in general. A significant proportion of the literature has focused on the pricing and market mechanisms of online platforms (Wang, 1993; Hammond, 2010, 2013; Waisman, 2018; Wei and Lin, 2017; Einav et al., 2018). Platform design and the adoption of pricing mechanisms improve the matching between the two sides of the market (Hitsch et al., 2010), better to facilitate transactions and increase platform profits. Typically, a platform chooses from an auction model (Prosper before December 2010, eBay), a posted-price regime (Prosper since 2011, LendingClub, Amazon, etc.), an auction model with a buy-it-now (BIN) option (eBay), dynamic pricing (Uber surge pricing), or a combination of multiple pricing schemes.[6] Several studies compare the market outcomes across different pricing schemes. The general finding is that each pricing mechanism has its strengths in certain respects while falling short in others. Auctions, for example, allow sellers and buyers to signal their private information and achieve efficiency through market forces but create more friction and decrease transaction volume. Posted prices, though convenient, can lead to inefficient outcomes (Wei and Lin, 2017).

Our study is unique because we clearly identify a pricing mechanism's cherry-picking opportunity and use this setting to study seller behavior and learning. We illustrate the adverse effects of a centrally designed pricing mechanism. In this sense, our work is similar to that of Backus et al. (2017), which documents the unintended consequences of the buy-it-now option on eBay: After bidders (buyers) are snipped off by buy-it-now buyers, they become frustrated and exit the market.[7]

The paper is organized as follows: Section 2 describes the three pricing mechanisms that were adopted by Prosper.com after its opening in 2006. Section 3 discusses data that we used in the study and provides basic summary statistics. Section 4 presents stylized facts that show evidence of platform mispricing and lender adjustment to new pricing rules. Section 5 is our main empirical investigation to document lender learning when there is platform mispricing. We also perform a set of robustness checks in Section 5 before we conclude in Section 6.

2 Prosper.com and Pricing Mechanisms

Our research context is Prosper.com: the earliest and second-largest peer-to-peer (P2P) lending platform (by loan origination volume to date) in the United States. Prosper has experimented with various pricing schemes since its inception in 2006. In particular, in

[6] eBay even allows NFL ticket sellers on the platform to choose from a menu of four different mechanisms: ascending-like auctions; hybrid auctions with a buy-it-now option; posted prices; and posted prices with an option for buyers to make offers to sellers, who can then engage in bargaining (Waisman, 2018).

[7] Backus et al. (2017) find that inexperienced bidders suffer disproportionately more from such behavioral biases as compared with experienced bidders, which agrees with our findings that inexperienced lenders are slower to adjust their investment strategy in response to a platform rule change.

December 2010, Prosper abandoned its previous auction model and adopted posted prices.[8] About 18 months later, Prosper switched again: this time from a credit-grade-specific fixed-rate mechanism to a scheme that allows flexible pricing within a certain credit grade. In this section, we describe the relevant pricing schemes that were used by Prosper.

2.1 Prosper Auctions

Prosper originally adopted an auction mechanism when it first opened to the public in April 2006. In a Prosper auction, a borrower posted a loan request to borrow a specific amount of money, the purpose of the loan, and the maximum interest rate she was willing to accept. The borrower could also voluntarily provide credit-related information such as her monthly income. At the same time, Prosper obtained a copy of the borrower's credit profile from Experian – one of the three major credit reporting agencies – when she submitted an application to list her loan request. Prosper then published most of the credit information on a listing page, including a 20-point range of the borrower's credit score, the number of delinquencies in the last year, and her revolving credit balance. Once the listing was posted on the platform, lenders arrived, decided whether they would like to invest, and submitted bids by specifying the minimum interest rate (at which they would like to lend) and the dollar amount they were willing to lend (which had to be between a minimum acceptable amount and the requested amount). Lenders usually funded much less than the full amount of the loan request for the purpose of risk diversification and/or because of budget constraint. A listing was successful and would originate as a loan once it received sufficient funding within a predetermined period. The contract interest rate was then set by the lowest interest rate of the outbid lenders.[9]

In principle the auction model enables both sides of the market to signal their willingness

[8] Source: https://web.archive.org/web/20110312134825/http://blog.prosper.com/2010/12/30/exciting-new-enhancements-at-prosper/

[9] A lender was outbid for a listing if within a predefined period (usually 14 days), the funding requirement was fulfilled by other lenders, all of which accepted a lower interest rate than this lender. It was possible for a lender to be "partially outbid." For example, if lender A bid for 50% of a loan listing at 8% but lender B bid for 100% at 10% while the borrower's maximum interest was 15%, then after 14 days (assuming no other lenders bid for the same loan with a rate less than 10%) the loan originated, and each of the two lenders funded 50% of the loan at the rate of 10% as 50% of lender B's bid was outbid by lender A. In addition, if none of the bidders are outbid or all losing bidders bid at the maximum interest rate that was set by the borrower, the contract interest rate would be the borrower's maximum interest rate.

to pay, and the interest rate is determined at the "market clearing price." Therefore, conditional on competitive loan demand and supply and on both sides having perfect information, the auction model should lead to efficient equilibrium interest rates and loan origination volume (Wei and Lin, 2017; Einav et al., 2018). However, as claimed by Prosper in its post about the regime change,[10] the auction rule was too complex, and the bidding process was time consuming – especially for inexperienced lenders. So, this auction-based price discovery mechanism prolonged the funding process and impeded the speed advantage made possible by online platforms.

2.2 Posted Prices Regime I: Coarse, Single-Price Regime

On December 20, 2010, Prosper abandoned the auction mechanism in favor of a posted-price scheme. Prosper claimed that one of its motivations was "to facilitate quick deployment of funds."[11] Under the new pricing scheme, the platform evaluated borrower risk and sorted the borrowers into one of seven risk grades: "Prosper Ratings." A different interest rate was set for each of the seven risk grades, which were identified as: AA, A, B, ..., and HR, where an "AA" grade meant least risky and an "HR" listing was most risky. To map each loan request to a Prosper rating, Prosper used a proprietary algorithm to calculate the "estimated loss rate" based on the borrower's FICO score and the payment performance of a group of similar borrowers on Prosper.com.[12] The rating system was a "step function" of the Prosper-calculated estimated loss rate, which indicated the default risk of the particular listing. Table 1 provides an example of Prosper's pricing table at the beginning of 2012. The interest rates are for 36-month loans by borrowers who had no previous Prosper loans.

[Insert Table 1 about here.]

From Table 1, we first note that there is no overlap in the estimated loss rate across Prosper ratings. More importantly, Table 1 reveals the coarseness of Prosper's mapping from risk categories (typically 2% – 3%) to interest rates. For example, a borrower with a

[10]Source: https://www.lendacademy.com/prosper-com-ending-their-auction-process-dec-19th/

[11]Source: https://web.archive.org/web/20110312134825/http://blog.prosper.com/2010/12/30/exciting-new-enhancements-at-prosper/

[12]The similarity is defined over the delinquency history and default/prepayment tendency of borrowers.

1.99% loss estimate would pay an interest rate of 6.49%, while a borrower with a 2.0% loss estimate would pay 9.99%. The interest rate would be fixed once it was assigned to the loan listing. Unlike under the auction regime when the contract interest rate could be lower than the original asking interest rate, the preset interest rate under this new posted-price regime would not change through the funding process or the subsequent payment period (typically three years).

As is shown in Figure 1, at the summary page of an example loan listing, the Prosper rating of "A" is displayed at the center front, right next to the amount, the term limit, and the lender yield rate of the loan should it originate. The estimated loss rate, 2.50% for this loan listing, is displayed next to the letter grade, with smaller fonts, in a less prominent place, but still quite visible. As an "attentive" lender could easily see both the Prosper letter grade and the estimated loss rate, he should have taken advantage of this single-rate pricing scheme. An "A" listing with a 2% of estimated loss rate and another "A" listing with a 3.99% of estimated loss rate had the same interest rate of 9.99%. Choosing the listings with lower estimated loss rates within a credit grade is a dominant investment strategy, because this strategy diminishes the default risk while reaping the same level of promised returns.[13]

[Insert Figure 1 about here.]

2.3 Posted Prices Regime II: Fine, Variant-Price Regime

On July 20, 2012, Prosper made further changes to its posted-price regime. Instead of assigning a uniform interest rate to all loan listings within one Prosper rating, it offered a range of interest rates for listings with different estimated loss rates. Table 2 shows a sample pricing scheme that was used by Prosper during this period. The interest rates are for the same set of loan listings as in Table 1: 36-month loans by borrowers that had not originated any previous loans on Prosper. The interest rates within each Prosper rating could differ by 0.55% (Rating NR) – 4.25% (Rating C). This large difference in interest rates within each Prosper rating confirms our conjecture that listings within each risk grade are of different

[13]In Section 4.1 we provide more detailed discussions, and Figure 3 illustrates our main theoretical considerations.

quality and offering a single price might be suboptimal.

[Insert Table 2 about here.]

Figure 2 shows the changes in contract interest rates by Prosper rating over time. The figure covers a period from July 2010 to February 2013, during which timeframe Prosper users experienced all three pricing schemes: auctions, posted prices I, and posted prices II. For ease of comparisons across the three schemes, we show (funded) loans with 36-month maturity and with borrowers who had no prior Prosper loans. Not surprisingly, the contract interest rates under auctions can overlap with Prosper ratings. In sharp contrast, at any given point in time, under the single interest rate scheme, there is only one effective interest rate for each Prosper rating. In the last phase, although there is a range of interest rates in each Prosper rating, those ranges do not overlap with each other across Prosper ratings.

[Insert Figure 2 about here.]

3 Data and Samples

We obtained administrative records from Prosper.com, which covers all transactions in a period between Prosper's public inception in April 2006 and February 2013.[14] We have 447,234 completed loan requests—either funded or failed—in our data. Among them, 69,234 listings were funded and originated as unsecured personal loans. The overall success rate is about 15.6% ($= 69,234/447,234$).

For all loan requests (both failed and successfully funded), we observe all information that was shown on the listing page (as in Figure 1), which is also available to all potential lenders. For example, we observe the starting and closing time stamps; the loan amount that was requested; the interest rates; the Prosper rating of the loan listing; and the borrower's credit profile. In addition, we observe all bids (or investments in posted prices) and the

[14] After February 2013, Prosper significantly changed its data accessing policy. All historical bids and investments are hidden and new investment data are no longer available (source: https://web.archive.org/web/20130512072342/http://blog.prosper.com:80/2013/03/30/a-note-from-our-president-aaron-vermut-as-prosper-looks-to-the-future).

associated lenders. For funded loans, we know the eventual payment outcomes. The loans can be paid on time, paid off early, or defaulted (with numerous reasons such as bankruptcy).

We focus on the period from December 2010 to February 2013 in this study, which spans the two posted-price regimes. During this two-year period (December 2010 – February 2013), 60,759 listings were posted on Prosper.com, and 32,588 of those received sufficient funding to be initiated as unsecured personal loans. The success rate was much higher under posted prices: an overall ratio of 53.6%. Among all those posted-price listings, 41,238 were posted under the single rate regime. The success rate of these single-rate loan listings was roughly 54.2% ($= 22,334/41,238$). Under the variant-rate scheme, 19,521 loan requests compose our sample and the success rate for these listings was 52.5% ($= 12,254/19,521$).

We construct the sample for our analysis from these posted-price listings (both single-rate listings and variant-rate listings). In the main analysis, we study whether and how quickly lenders learn the "cherry-picking" opportunity in the pricing scheme. Therefore, a unit of observation is a lender-month combination. We choose the span of a month because it is a sufficiently long period for a lender to adapt and revise investment strategies. Table 3 summarizes the main variables that are used in our analysis. Our main sample consists of all lenders' monthly investment portfolios from December 2010 to July 2012: the period during which the single pricing mechanism prevailed.[15] In total, there are 149,883 monthly portfolios from 20,975 lenders. On average, lenders had roughly 42 months of experience on Prosper as of August 2012 (the end of our sample period). About 31% of the lenders were frequent lenders that had invested at least 10 months during our sample period. The average lender invested $7,757.33 through Prosper, while the median lender invested $750; this suggests a highly skewed distribution of total investment per lender: Most lenders were recreational investors who invested at a magnitude of no more than a thousand dollars, while a small number of institutional investors invested heavily (sometimes in millions) on Prosper.[16] In addition, the median lender invested in 19 different loan projects and her median bid size was $25.[17]

[15]The monthly portfolio consists only of investments in loan listings that eventually originated as loans.

[16]The largest lender – not surprisingly, an institutional investor – invested $38.4 million on Prosper during our sample period.

[17]The number of loan projects that a lender funded is roughly the same as the number of bids that the

Notably, there is a huge variation among lenders in the time span between when a listing was posted and when the investor decided to invest. On average, a lender's median bidding lag was 124.37 hours (about 5 days). However, the fastest lender placed her bid within 0.005 hours (18 seconds) of time.[18] Our dependent variables – the percentage number of a lender's bids on "plus loans" and the percentage amount that the lender invested in "plus loans" – are quantitatively similar.[19] For an average lender portfolio, 42% of number of bids (or 43% amount invested) went into plus loans.

[Insert Table 3 about here.]

4 Theoretical Considerations and Stylized Facts

4.1 Theoretical Considerations

The posted-price schemes provide us with a unique opportunity to study how lenders learn to take advantage of the "cherry-picking" opportunity in platform pricing. As was summarized in Section 2, as compared with the auction period, under the single-rate regime a lender's choice is simplified to accept or reject the interest rate that is preset by the platform given a bundle of loan characteristics. If lenders are sophisticated enough to take advantage of the opportunity, it will significantly affect both sides of the market and also the platform. When lenders strategically rush to fund the less risky listings within each Prosper rating, borrowers on the riskier spectrum within each rating grade will find it hard to get funded. If that happens, borrowers might respond by choosing outside options and leave the market. The aggregate effects of the interaction among lenders, borrowers, and the pricing schemes remain unclear.

Figure 3 provides a visualization of the market inefficiency that is driven by the single-price scheme. The figure shows a hypothetic market equilibrium for a specific credit grade.

lender made: We consider only bids for listings that eventually originate as loans and that it is of negligible probability that a lender bid for the same listing for multiple times.

[18] Some of the fastest lenders, most likely institutional lenders, use the application program interface (API)—a set of web-based tools Prosper provides for building software—to interact programmatically with Prosper's loan database and place bids in real time.

[19] We define "Plus loans" as loans with less than the median estimated loss within each Prosper rating, which are less risky given the Prosper rating (see Subsection 4.2).

The horizontal axis is the amount requested of loan listings (q), and the vertical axis is the interest rate of loan listings (r). We define lenders as the supply side—providing funds—and borrowers as the demand side.

Assume that there are three levels of risk within the grade: safe, medium and risky. The supply curve of risky loan listings S_{risky} is leftmost, because at any given loan amount q lenders need to be compensated by a higher interest rate. In contrast, the demand for those risky loan listings D_{risky} lies rightmost, because at any given loan amount q these risky borrowers are willing to pay a higher interest rate.

If interest rates can vary with the riskiness of loans, the equilibria are E_{risky}, E_{mid}, and E_{safe}, and the market clearing interest rates for the three levels are $r_{\text{risky}} > r_{\text{mid}} > r_{\text{safe}}$. However, market inefficiency is likely to emerge under the single-price regime. To see this, assume the platform sets interest rate r_{mid} for all loan listings within the grade. At r_{mid}, the loan volume supplied for risky listings is QS_{risky}, which will be smaller than the volume demanded QD_{risky}. On the other hand, the volume supplied for safe listings QS_{safe} will be greater than the quantity demanded QD_{safe}. In essence, there is excess supply for safe loan listings but a supply shortage for risky listings.

We should see lenders rush to fund safe listings over risky ones. Some risky borrowers within each rating grade, who would have been funded (likely at higher interest rates) under a variant-price regime, will fail to be funded and will leave the market. Similarly, suppliers who would have been willing to make loans at higher rates will leave the market. The next three subsections provide stylized facts that support these outcomes.

[Insert Figure 3 about here.]

4.2 Platform Mispricing and the Timing of Lender Arrival

We begin with evidence to show the existence of excess (lending) supply of less risky loans and excess (borrower) demand for risky ones. Given the Prosper rating, we call the less risky loans within the rating grade "plus loans" (and "minus loans" on the other end of the spectrum). In our definition, a plus loan has an estimated loss rate that is lower than the median estimated loss rate of all loans at the same Prosper rating. For example, the range of

"A" loans' estimated loss rate is 0.02 – 0.04. The median rate for these loans in our sample is 0.033. Thus, we define plus "A" loans as being those with an estimated loss rate that is lower than 0.033. We define plus loans in other Prosper ratings in a similar manner.[20]

Our theoretical considerations predict that there exists excess (lending) supply of plus loans and excess (borrower) demand for minus loans. Therefore, lenders should rush to fund the plus loans as loans are on a "first-come-first-serve" basis under the posted-price mechanisms: A listing will be funded by the order of lender arrival and initiated as an amortized personal loan immediately upon full funding. We compare the difference in lenders' arrival time (or bidding lag time) for plus and minus listings under the single-price regime with the same difference under the variant-price regime. We should see that lenders arrive earlier for plus loans than for minus loans under a single-price regime. In contrast, under the variant-price regime, plus loans do not strictly dominate minus loans, so lenders' arrival timing should not differ significantly.

Figure 4 clearly demonstrates that the pattern of lender arrival time is consistent with our prediction. The left panel depicts the distributions of lender arrival time – measured in the number of days of bidding lag – for plus loans and minus loans under the coarse single-price regime. The right panel displays the same distributions but for loans under the fine variant-price regime. Clearly, lenders arrived on average much earlier for plus loans than for minus loans under the single-price regime (the left panel of Figure 4). There is, however, little difference between the two distributions under the fine variant-price regime (the right panel of Figure 4).

For the single-price regime, roughly 30% of investments in plus loans were placed within 12 hours of the listing being posted, and 40% were placed within 24 hours. In contrast, only 20% of investments in minus loans were placed in the first 12 hours, and 27% were placed in the first 24 hours. Under the fine variant-price regime, however, about 33% of investments were placed within the first 12 hours for both plus and minus loans.

[Insert Figure 4 about here.]

[20]We will use this definition of "plus" (or "minus") loans throughout the paper. Our formal empirical tests that are reported in Section 5 are based on these definitions.

4.3 Platform Mispricing and Funding Probabilities

The differences in lender arrival times that were reported in the last section should lead to differences in the probability of a listing's being funded. Figure 5 depicts the combinations of a listing's funding probability (vertical axis) and its estimated loss rate (horizontal axis) under the single- and variant-price regimes. We divide listings at each Prosper rating into four bins according to their estimated loss rate and then plot the average funding probability for each bin. For example, listings at Prosper rating "A" have an estimated loss rate that ranges from 0.02 to 0.04. We divide these listings into four bins: Each bin contains listings with estimated loss rates of $[0.02, 0.025)$, $[0.025, 0.03)$, $[0.03, 0.035)$, and $[0.035, 0.04)$, respectively. A point in the "A" range in Figure 5 shows the average funding probability of the loans in the corresponding estimated loss range. We report funding probabilities under the single-price regime as solid black dots and those under the variant-price regime as hollow black circles.

[Insert Figure 5 about here.]

Figure 5 shows first that, at any given Prosper rating, the funding probabilities under the single-price regime are much more dispersed than those under the variant-price scheme. As an example, the average funding probability of the least risky "A" listings is about 83.2%. In sharp contrast, the same probability for the riskiest "A" listings is about 43.8%, which is almost half of the probability for the safer listings in the same credit grade.

Second, at any given rating, the funding probability decreases with an increase in the estimated loss rate under the single-price regime. In contrast, the funding probability stays relatively constant across bins under the variant-price scheme.

Last but not least, above and below the estimated loss rate cutoffs that separate Prosper ratings, the funding probability of less risky loans is much lower than that of more risky loans under the single-price regime. For instance, the loss rate cutoff that separates "AA" listings and "A" listings is 2%. Right below this cutoff, the funding probability of the most risky "AA" listings is about 0.467, while the funding probability of the least risky "A" listings (right above the loss rate cutoff) is 0.832.

This discontinuity in funding probabilities suggests that the price mechanism fails to adjust the demand and supply: The least risky "A" listings have an interest rate of 9.99%, and the most risky "AA" listings have an interest rate of 6.49%, although these two sets of listings are very similar in intrinsic risk (as measured by the estimated loss rate).

These findings suggest that the single-price regime was inefficient. The lack of price variation within a rating grade leads to distortions in the funding probabilities of listings at a given Prosper rating. This is consistent with our theoretical discussion in Section 4.1. However, these observed lender responses to the platform "mispricing" are justified only if the "less risky" loan listings as measured by the estimated loss do indeed perform better when they originate as loans. In the next subsection we examine whether there is a premium in terms of loan performances for lenders to invest in less risky loan listings within each grade.

4.4 Platform Mispricing and Loan Performance

Is it rational for lenders to react strategically to the cherry-picking opportunity in Prosper's pricing mechanism? To answer this question, we study default risk as a loan performance to test whether lenders should prefer the less risky loans at a given rating. More specifically, if the estimated loss rate is a good indicator of the default risk, then given the promised interest rate, lenders should indeed prefer the less risky loans over those on the other end of the risk spectrum.

We face a constraint that our observation of payment outcomes is right-censored by February 2013 (the last period of our sample). Because most of the loans amortize in 36 or 60 months, we do not observe the final outcome of all loans. Instead, we use the rate of being delinquent at an early stage of the payment process as a loan performance proxy. Specifically, we code a loan as being delinquent at a period that is relatively early if the borrower missed at least one payment during the first four payment cycles (usually by months) for comparability considerations. This proxy measure is used in the literature (such as Butler et al. (2016), Wei and Lin (2017)).

Figure 6 plots the relationship between the delinquent-early rate and the estimated loss rate before and after the pricing scheme change. Unlike the funding probability plot in

Figure 5, the early delinquency rate increases with the estimated loss both within and across Prosper ratings. The pattern holds for both coarse and fine pricing schemes. For example, when we compare Figure 5 with Figure 6, under the single-price regime the safest "A" loans are only slightly less likely to be delinquent early, but these listings are almost twice as likely to get funded as the riskiest "A" loans.

Second, there is also no evidence of a significant jump in the early delinquency rate for loans that are just across the estimated loss boundaries that separate Prosper ratings. In other words, the estimated loss rate serves as a relatively precise measure of the risk of loan listings on Prosper.com. As lenders can observe the estimated loss in addition to the Prosper rating of each loan listing (see Figure 1), their systematic preference for listings with a lower estimated loss in each Prosper rating is justified by the better performance of the loans that originated from these listings.

[Insert Figure 6 about here.]

5 Lender Learning

In the previous section we presented stylized facts that suggest that lenders exploited the "cherry-picking" opportunity in Prosper's single-price regime. Did all lenders – which are highly heterogeneous in their experiences and strategic ability – immediately realize the opportunity of arbitrage after Prosper suddenly switched from the auction-based regime? In this section, we use a regression framework to study how lenders adjusted their investment portfolios to respond to the new, single-price mechanism. Did lenders quickly tilt their portfolios toward plus loans? If not, how fast did lenders learn? How differentially did they learn?

5.1 Empirical Strategy and Predictions

In our main empirical specification, we construct a lender-month panel of monthly investment portfolios. The main variable to be explained is the fraction of monthly investment amount made to the less risky loans in each Prosper rating. We also calculate the fraction of monthly bids submitted to the plus loans in an alternative specification.

Our main regression equation is:

$$\%\text{ plus loans}_{jt} = \alpha + \beta_1 T_t + \beta_2 T_t^2 + \xi_j + \epsilon_{jt}, \tag{1}$$

where % plus loans$_{jt}$ is the percentage of lender j's monthly number of bids (or the monthly amount of dollars) invested in plus loans in month t. Note that these are measures of a lender's newly generated lending activities (not her portfolio holdings as of a particular month). T_t is the number of months elapsed since December 2010 when the single-price pricing scheme was implemented. We run regressions with and without a quadratic form of the elapsed time T_t^2 to capture a potential nonlinearity in the learning rate over time.[21] We include lender fixed effects ξ_j to control for time-invariant lender level heterogeneity. Lastly, ϵ_{jt} are normally distributed error terms, which are *i.i.d.* across lenders and over time.

The coefficients β_1 and β_2 capture the pattern of lender learning. With learning we expect that lenders will gradually increase the shares of plus loans in their portfolios. Therefore, our conjecture is that β_1 is positive. We also expect the learning process to "slow down" eventually because, first, the fraction of plus loans has a natural upper bound of 100%. Second, not all lenders will be able to invest in plus loans due to intense competition among lenders. Instead, they may have no choice but to invest their available funds in riskier loans. Therefore, our conjecture is that β_2 is negative.

We also study the role of lender heterogeneity in this learning process. As shown in Table 3, lenders differ in many dimensions, including their investment volume, experience on the platform, bidding strategies, and diversification strategies. We argue that lenders may also be different in their ability to capture profit opportunities in a changing market. For example, more experienced lenders may be swifter to recognize a financial opportunity; and active lenders may better understand platform rules. To capture the heterogeneity of lender learning, we explore whether lender characteristics play any moderating role in the learning

[21] In the Appendix, we report results from an alternative specification. Instead of the quadratic form as in Equation (1), we estimate a specification with the logged number of months, $\log(T_t)$. We can reach qualitatively the same conclusion using the alternative specification.

process.

We adjust the main specification, Equation (1), by adding lender characteristics and the interaction terms with the number of elapsed months:

$$\% \text{ plus loans}_{jt} = \alpha + \beta_1 T_t + \beta_2 T_t^2 + \mathbf{X_j}\boldsymbol{\gamma} + (\mathbf{X_j} \cdot T_t)\boldsymbol{\delta} + \xi_j + \epsilon_{jt}. \tag{2}$$

The two dependent variables remain the same (in the two separate regressions), and we retain both T_t and T_t^2 to capture the nonlinearity in the learning rate. We include $\mathbf{X_j}$, a vector of time-invariant lender characteristics that includes: the log of total investment; bidding speed; the Herfindahl-Hirschman Index (HHI) of a lender's investment portfolio; frequent investor status; and lender experience.

First, the log of total investment is the natural log of a lender's total investment volume during our study period. We define the "bidding speed" as the inverse of the median time that elapsed between the time of a listing's being posted and the time of the first investment by a lender. The larger the value of this characteristic, the faster the lender invests in a listing.

A lender's diversification strategy may play a role in her learning. We use the HHI of a lender's portfolio as a measure of the distribution of shares for individual investments of the particular lender.[22] We are also interested in how a lender's activeness may affect the learning rate. We define a "frequent lender" status to indicate whether a lender had been active in lending in at least ten months during our study period. Last, we define the lender experience as the number of months passed since it registered on the Prosper website. Note that in specifications with lender-level fixed effects, the level effect of $\mathbf{X_j}$ will be absorbed into lender-level fixed effects but the interaction effect between $\mathbf{X_j}$ and T_t will not.

In this specification, β_1 and β_2 again capture the basic pattern of learning. The coefficients of the interaction terms, $\boldsymbol{\delta}$, measure the heterogeneity in lender learning (or, the moderating role of lender characteristics).

[22]Specifically, the $\text{HHI of investment}_j$ for lender j is defined as: $\text{HHI of investment} = \sum_{n=1}^{N_j} (\text{investment in loan } n/\text{total investment of lender } j)^2$, where n denotes lender j's nth loan invested and N_j is the total number of such loans.

5.2 Main Results: Baseline

Table 4 reports the regression results of Equation (1). Columns (1) – (4) are various specifications using the percentage of bids in plus loans in a month as the dependent variable. We examine specifications with and without the square term of time elapsed since December 2010 and with and without lender fixed effects. The results are quite consistent across specifications. In a similar manner, columns (5) – (8) report the regressions with the percentage of the dollar amount invested in plus loans in a month as the dependent variable. The results are, again, robust across specifications and consistent with the findings using the percentage of bids as the dependent variable.

[Insert Table 4 about here.]

First, all estimates suggest that an average lender does increase the fraction of his portfolio in plus loans over time. The coefficients for the number of months elapsed are all positive and statistically significant. This implies that the lender has learned over time the cherry-picking opportunity in Prosper's single-price regime and adjusted his portfolio towards the less risky spectrum.

Numerically, the specifications without the squared time elapsed – columns (1) – (2) and (5) – (6) – indicate that over time the lender increased the fraction of its portfolio in plus loans by roughly 0.4 percentage points each month. This translates to a growth of about 5 percentage points in the fraction of plus loan investment annually.

Second, the results reported in our main specifications – columns (3) – (4) and (7) – (8) – suggest that the learning process is by no means linear over time. Particularly, although the coefficients for the time elapsed term are still positive and statistically significant, the coefficients for the squared term are consistently negative across specifications. This implies that the rate of learning diminishes over time. As we hypothesized in Section 5.1, we attribute the diminishing learning to a hard cap on the fraction (it cannot be greater than 100%) and intense competition in the plus loans (as all lenders gradually learn about the cherry-picking opportunity).

These results allow us to calculate the time until a typical lender fully exploits the cherry-picking opportunity in the pricing scheme and stops learning. In other words, the fraction of plus loans in his portfolio stops increasing when he fully takes advantage of the cherry-picking opportunity. To calculate this "stopping" point, we let the marginal effect of adding a month (to his learning process) be equal to zero. Specifically, the marginal effect of time is $\partial(\%\text{ plus loans}_{jt})/\partial T_t = \hat{\beta}_1 + 2\hat{\beta}_2 T_t$, in which $\hat{\beta}_1$ and $\hat{\beta}_2$ are estimates of the two corresponding coefficients. Using the estimates from our main specifications–column (4) and column (8) in Table 4 – we find that it takes approximately 16 – 17 months for the lender to learn fully and take advantage of the cherry-picking opportunity.[23]

5.3 Heterogeneity in Learning

With regard to the heterogeneity in learning, Table 5 reports the regression results of equation (2) from various specifications. First, the coefficients of the time elapsed and its squared term are, again, consistent with the main findings in Table 4. This suggests that – controlling for lender heterogeneity – the learning pattern and the diminishing marginal learning still hold. Column (2) and column (4) of the table report the results with lender fixed effects (the terms of lender characteristics are thus dropped), and columns (1) and (3) report the regressions without lender fixed effects.

[Insert Table 5 about here.]

The estimated coefficients for the interaction terms suggest that significant heterogeneity exists in learning. First, by controlling for other characteristics such as lender experience with Prosper.com, lenders with larger portfolios seem to immediately capture the cherry-picking chance, as indicated by the positive coefficient of log(total investment). This suggests that these larger lenders were better at exploiting the cherry-picking opportunity than smaller lenders. Over time, these larger lenders adjust their investment down in plus loans as suggested by the negative and statistically significant coefficient of the interaction term, time $\times$ log(total investment). It can be attributed to the fact that lenders with larger

[23] To see this, using the estimates reported in column (4) of Table 4, the marginal effect of time is $\hat{\beta}_1 + 2\hat{\beta}_2 T_t = 0.0105 - 0.00063 T_t$. Setting it equal to zero gives us $T_t \approx 16.67$. From the estimates in column (8), $T_t \approx 17.04$. The similarity in these two sets of estimates supports the robustness of our results.

portfolios started off with larger fractions of plus loans, so they simply do not have much "room" left in their portfolios to hold more plus loans (relative to smaller lenders). These findings suggest distinct learning styles by large and small lenders on Prosper.com.

Similarly, different learning patterns exist based on lenders' diversification strategy. A lender with a more concentrated portfolio—larger portfolio HHI—starts off with larger shares of plus learns, as indicated by the positive coefficient of HHI of investment. However, the negative and statistically significant coefficients for the interaction term, time $\times$ HHI of investment, indicate that a lender with concentrated portfolio adjusts the share of plus loans downward over time. In contrast, a lender with a more diversified portfolio starts with a smaller fraction of plus loans but adjust their portfolio toward these "cherry-picking" opportunities gradually. These findings are consistent with the fact that an investor with a more focused portfolio pays more attention to the specific loans to consider and is better at spotting these "cherry-picking" opportunities immediately after the pricing regime change. An investor with a diversified portfolio, to the contrary, pays more attention to smoothing investment across credit grades rather than to "cherry-picking" the best loan within each grade. Therefore, a diversification-inclined lender might fail to capture the "cherry-picking" opportunity right after the platform changed the pricing mechanism. However, as these lenders gradually find out that the plus loans in each grade perform better they adjust their portfolio toward the plus loans over time. [24]

Last, as a comparison, the estimated coefficients for the term, time $\times$ lender experience in months, are positive and statistically significant, which implied that a lender that had registered for a longer period picks up the mispricing opportunity more quickly. The negative and statistically significant coefficients for the term, lender experience in months, as in column (1) and column (3), indicate that these lenders started with smaller fractions of plus loans in their portfolio, potentially because these lenders were more likely to invest in a more diversified portfolio. However, being more experienced investors on Prosper.com, they realized the cherry-picking opportunity and adjusted their portfolios significantly faster.

[24] The other characteristics that we consider – the bidding speed (measured by the inverse of time until the first commitment in a funding process), and the frequent-lender status – do not play significant roles in moderating learning patterns.

5.4 Further Discussions and Robustness

In this section we perform a set of robustness checks to ensure that our main findings are robust to alternative specifications and explanations. In addition to the robustness checks reported in this section, we also run fractional logit regressions and two-sided Tobit regressions based on our main specification. We report the tables in the Appendix, and the results are qualitatively the same.

Infrequent lenders: Some lenders were not very active on the platform during our study period. In our sample, 14,388 – roughly 69% of all 20,975 lenders – made investments in fewer than 10 months during our study period. These lenders may be "recreational" investors, and their investment objectives may not be profit maximization. We re-estimate specifications in Table 5 to examine whether our results still hold by excluding these infrequent lenders.

The results are reported in Table 6. Comparing Table 6 with Table 5, we first notice that the signs of the coefficients for the time elapsed term stay the same, but the magnitudes are larger for the frequent lender subsample. This implies that frequent lenders learn faster than do infrequent lenders. This is natural because frequent lenders, by participating in this online market more frequently, are more exposed to the cherry-picking opportunity in the single-price regime; therefore, they are more likely to learn about the pricing opportunity more quickly. These results with regard to learning heterogeneity are also qualitatively and quantitatively similar to those in Table 5.

[Insert Table 6 about here.]

Definition of "plus" loans: In the main specifications, we define plus loans to be those with estimated loss rates that are smaller than the median estimated loss of loans in the same category. We conduct robustness check to examine whether the findings still hold using different definitions of plus loans. Specifically, we examine two new thresholds: the 25th percentile and 10th percentile in estimated loss rates of loans in the same category. We define new plus loans as those with an estimated loss rate less than the 25th percentile or the 10th percentile. We repeat the regressions of Equation (2).

Table 7 reports the results. Columns (1) and (2) report results for the 25th percentile specification, and the last two columns correspond to the 10th percentile case. The overall learning patterns still hold; however, the results show that lenders learn at an increasing pace, as suggested by the positive estimate on $time^2$. Indeed, as we narrow the definition of plus loans, the loans categorized as "plus" are even more preferable than when plus loans are only loosely defined. Therefore, it is likely that lenders learn and increase their holdings of these premium loans faster over time.

[Insert Table 7 about here.]

The fine variant-price regime: As mentioned earlier in the paper, Prosper increased the granularity in its interest rate structure as a correction for the flawed, coarse single-price regime. Under the new finer variant-price regime, there is no clear advantage to pursue plus loans because the interest rates that are assigned to these loans are better adjusted to reflect the difference in inherent risk among loans in the same rating.

We repeat the regressions of Equation (2) with an alternative sample of all investment portfolios under the variant-price regime. The sample covers a period between July 20, 2012 and February 2013. We expect that after Prosper switched to the variant-price regime, lenders would change investment strategy and would not continue to pursue plus loans.

Table 8 reports the results. First, the coefficients for the time elapsed term are statistically insignificant. Second, the coefficients for the squared time elapsed are negative and statistically significant, which suggests that lenders may eventually decreased their holdings of plus loans. This is a rebound from their previous investment strategy of increasing holdings of plus loans under the coarse single-price regime. As plus loans are no longer preferable, the lenders' new investment direction will dilute the share of their holdings of plus loans.

Among different lenders, again the larger, more diversified lenders responded to the new pricing mechanism immediately, but the more experienced ones were much quicker to reduce their plus-loan holdings as time elapsed.

[Insert Table 8 about here.]

6 Concluding Remarks

Using data from a major P2P lending platform, Prosper.com, we study a unique period when the platform assigned an interest rate for all of its personal loan requests. During this period, Prosper started with a single-price mechanism under which the same interest rate was assigned to loans with the same Prosper rating but quite different inherent risks. Investigating lenders' portfolio compositions under the coarse posted-price regime, we find that lenders weighed their portfolios towards the less risky spectrum within a given Prosper rating. We also find heterogeneity in the speed of learning by lender experience in the market, the size of their investment, and their diversification strategies. Interestingly, our estimates suggest that it would take about 16 – 17 months for a lender to learn fully and take advantage of the flawed pricing mechanism. This is roughly when Prosper switched to a new pricing regime in which Prosper assigned a range of interest rates corresponding to much finer risk levels at each Prosper rating.

Prices play a central role in market equilibration. The processes of demand and supply largely determine the equilibrium prices to match buyers and sellers. However, how long it takes market participants—most importantly buyers and sellers—to adjust to new pricing regimes (or any type of new market rules) and reach equilibrium is an issue at the intersection of behavioral economics and industrial organization on which there is little research.

We document a setting where a platform's pricing mechanism is flawed and market participants actively react to this flaw. More important, it takes time for market participants to adjust their strategies, and the road to equilibrium is a long, steady process that does not happen overnight.

The documentation of these facts fills in the gaps in our knowledge about how market participants interact with each other in the adjustment period toward a long-run market equilibrium. We hope that these regularities from the field help inform how researchers can model firm behavior that deviates from the fully rational benchmark.

Our findings also shed light on our understanding of platform strategy: As the market maker of two-sided markets, platforms often assign prices at which buyers and sellers transact. Most P2P lending platforms adopt a Prosper-type fixed rate mechanism. For example, Uber determines the base rate and rush-hour premium for rides based on its proprietary algorithm.

Prosper's mispricing episode is an example where the market maker did not accurately forecast investor response to its major rule change. In other words, Prosper demonstrated a lack of perfect foresight: an important source of behavioral biases that we often observe in individual decision-making.

When a new market mechanism is adopted without imperfect foresight, participant strategy may adversely affect market outcomes. In the Prosper case, some lower-risk borrowers (although they are at the risky end of the spectrum of their Prosper rating) may not be efficiently matched with investors and are likely eventually be driven out of the platform under the single-price mechanism. This is detrimental to the platform and its long-term viability.

Our findings suggest that platforms should account for participants' strategic reactions when designing the market place or when adopting new rules.

Table 1: Posted Prices Phase I—Single Interest Rate within a Prosper Rating

Prosper Rating[a]	Estimated Loss (%)	Borrower Rate (%)[b]
AA	0.00 – 1.99	6.49
A	2.00 – 3.99	9.99
B	4.00 – 5.99	14.49
C	6.00 – 8.99	20.49
D	9.00 – 11.99	25.52
E	12.00 – 14.99	30.58
HR	$\geq$ 15.00	31.77

[a] *Source:* The web archive scrape Prosper.com web pages over time. The interest-rate information that is presented in this table can be found at https://web.archive.org/web/20120107115713/http://www.prosper.com:80/loans/rates-and-fees/.

[b] These are the interest rates for 36-month loans by borrowers who have had no previous Prosper loans. This pricing table was posted on the Prosper website on January 7, 2012.

Table 2: Posted Prices Phase II—Variant Interest Rates within a Prosper Rating

Prosper Rating[a]	Estimated Loss (%)	Borrower Rate (%)[b]
AA	0.00 – 1.99	6.04 – 8.49
A	2.00 – 3.99	9.24 – 12.99
B	4.00 – 5.99	13.59 – 14.79
C	6.00 – 8.99	17.34 – 21.59
D	9.00 – 11.99	21.99 – 25.66
E	12.00 – 14.99	26.39 – 30.06
HR	$\geq$ 15.00	30.79 – 31.34

[a] *Source:* The web archive scrape Prosper.com web pages over time. The interest-rate information that is presented in this table can be found at https://web.archive.org/web/20130806015207/http://www.prosper.com/loans/rates-and-fees/.

[b] These are the interest rates for 36-month loans by borrowers who had no previous Prosper loans. This pricing table was posted on the Prosper website on August 6, 2013.

Table 3: Summary Statistics of Variables

Variable	Mean	s.d.	Min.	Median	Max.
lender-month level					
% number of bids for plus loans	0.42	0.36	0	0.38	1
% amount invested for plus loans	0.43	0.37	0	0.38	1
N			149,883		
lender characteristics					
is frequent lender	0.31	0.46	0	0	1
lender experience (in months)	41.85	23.23	1	50	82
total investment (in $)	7,757.33	276,024.50	25	750	3.84e+07
total number of bids	86.43	264.70	1	19	7,480
median bid (in $)	50.72	125.70	25	25	12,000
median bidding lag (in hours)	124.37	77.47	0.01	113.34	335.68
bidding speed	0.11	1.83	0.00	0.01	211.76
HHI of investment	0.19	0.28	0.00	0.06	1
N			20,975		

Table 4: Main Results: Baseline Regressions

Dep. Var.	% number of bids for plus loans				% amount invested for plus loans			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
time	0.00404***	0.00422***	0.0135***	0.0105***	0.00417***	0.00434***	0.0135***	0.0106***
	(0.00017)	(0.00030)	(0.00072)	(0.00078)	(0.00017)	(0.00030)	(0.00072)	(0.00079)
$time^2$			-0.00047***	-0.00032***			-0.00047***	-0.00031***
			(0.00003)	(0.00004)			(0.00003)	(0.00004)
constant	0.383***	0.381***	0.351***	0.360***	0.382***	0.381***	0.351***	0.360***
	(0.00204)	(0.00317)	(0.00318)	(0.00378)	(0.00206)	(0.00318)	(0.00319)	(0.00379)
Lender FE	No	Yes	No	Yes	No	Yes	No	Yes
N	149,884	149,884	149,884	149,884	149,884	149,884	149,884	149,884
R^2	0.004	0.004	0.005	0.005	0.004	0.005	0.005	0.005

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5: Results: Heterogeneity in Learning

Dep. Var.	% number of bids for plus loans		% amount invested for plus loans	
	(1)	(2)	(3)	(4)
$time$	0.0207***	0.0212***	0.0199***	0.0201***
	(0.00136)	(0.00231)	(0.00137)	(0.00232)
$time^2$	-0.00033***	-0.00026***	-0.00033***	-0.00025***
	(0.00003)	(0.00004)	(0.00004)	(0.00004)
$log(total\,investment)$	0.0354***	-	0.0349***	-
	(0.00159)		(0.00160)	
$bidding\,speed$	0.00237	-	0.00239	-
	(0.00313)		(0.00314)	
$HHI\,of\,investment$	0.142***	-	0.140***	-
	(0.0205)		(0.0206)	
$is\,frequent\,lender$	0.0107*	-	0.0113*	-
	(0.00533)		(0.00536)	
$lender\,experience\,in\,months$	-0.00225***	-	-0.00226***	-
	(0.00011)		(0.00011)	
$time \times log(total\,investment)$	-0.00223***	-0.00232***	-0.00212***	-0.00218***
	(0.00013)	(0.00024)	(0.00013)	(0.00024)
$time \times bidding\,speed$	0.00045*	0.00027	0.00045*	0.00025
	(0.00022)	(0.00033)	(0.00022)	(0.00035)
$time \times HHI\,of\,investment$	-0.0103***	-0.0294***	-0.0100***	-0.0291***
	(0.00188)	(0.00556)	(0.00188)	(0.00557)
$time \times frequent\,lender$	0.00042	-0.00067	0.00032	-0.00074
	(0.00043)	(0.00079)	(0.00043)	(0.00080)
$time \times lender\,experience\,in\,months$	0.00016***	0.00017***	0.00016***	0.00017***
	(0.00001)	(0.00002)	(0.00001)	(0.00002)
$constant$	0.181***	0.373***	0.186***	0.373***
	(0.0143)	(0.00393)	(0.0144)	(0.00395)
Lender FE	No	Yes	No	Yes
N	149,884	149,884	149,884	149,884
R^2	0.015	0.010	0.015	0.010

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6: Robustness: Excluding Infrequent Lenders

Dep. Var.	% number of bids for plus loans		% amount invested for plus loans	
	(1)	(2)	(3)	(4)
time	0.0270***	0.0253***	0.0260***	0.0239***
	(0.00209)	(0.00337)	(0.00212)	(0.00338)
$time^2$	-0.00027***	-0.00022***	-0.00026***	-0.00022***
	(0.00004)	(0.00004)	(0.00004)	(0.00005)
$log(total\, investment)$	0.0451***	-	0.0450***	-
	(0.00224)		(0.00228)	
$bidding\, speed$	0.0276***	-	0.0278***	-
	(0.00508)		(0.00523)	
$HHI\, of\, investment$	1.000***	-	1.028***	-
	(0.173)		(0.176)	
$lender\, experience\, in\, months$	-0.00252***	-	-0.00252***	-
	(0.00014)		(0.00014)	
$time \times log(total\, investment)$	-0.00305***	-0.00299***	-0.00294***	-0.00284***
	(0.00019)	(0.00033)	(0.00020)	(0.00033)
$time \times bidding\, speed$	-0.00106***	0.000162	-0.00107***	0.000126
	(0.00031)	(0.00041)	(0.00032)	(0.00045)
$time \times HHI\, of\, investment$	-0.0854***	-0.0852***	-0.0851***	-0.0831***
	(0.0149)	(0.0235)	(0.0151)	(0.0234)
$time \times lender\, experience\, in\, months$	0.00018***	0.00019***	0.00018***	0.00019***
	(0.00001)	(0.00002)	(0.00001)	(0.00002)
constant	0.111***	0.385***	0.113***	0.385***
	(0.0228)	(0.00421)	(0.0232)	(0.00424)
Lender FE	No	Yes	No	Yes
N	98,350	98,350	98,350	98,350
R^2	0.015	0.012	0.015	0.012

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7: Robustness: Alternative Definitions of “Plus” Loans

Dep Var. % number of bids for plus loans:	less than 25 quantile estimated loss		less than 10 quantile estimated loss	
	(1)	(2)	(3)	(4)
time	0.00723***	0.00296	0.00136**	0.00062
	(0.00109)	(0.00165)	(0.00048)	(0.00075)
$time^2$	0.00044***	0.00056***	0.00016***	0.00018***
	(0.00003)	(0.00003)	(0.00001)	(0.00002)
$log(total\,investment)$	0.0148***	-	0.00225***	-
	(0.00119)		(0.00051)	
$bidding\,speed$	0.00444	-	-0.00034	-
	(0.00395)		(0.00025)	
$HHI\,of\,investment$	0.0664***	-	0.0144*	-
	(0.0148)		(0.00625)	
$is\,frequent\,lender$	0.00543	-	0.00440*	-
	(0.00373)		(0.00172)	
$lender\,experience\,in\,months$	-0.00055***	-	-0.00017***	-
	(0.00008)		(0.00004)	
$time \times log(total\,investment)$	-0.00034**	-0.00008	-0.00025	-0.00002
	(0.00011)	(0.00017)	(0.00005)	(0.00008)
$time \times bidding\,speed$	0.00034	-0.00028	0.00006	0.00023
	(0.00027)	(0.00045)	(0.00003)	(0.00018)
$time \times HHI\,of\,investment$	0.00144	0.00782	-0.00185*	-0.00348
	(0.00156)	(0.00433)	(0.00076)	(0.00196)
$time \times frequent\,lender$	0.00133***	0.00165**	-0.00035*	-0.00035
	(0.00033)	(0.00053)	(0.00017)	(0.00028)
$time \times lender\,experience\,in\,months$	-0.00002**	-0.00002*	0.00001	0.00001*
	(0.000007)	(0.00001)	(0.000004)	(0.000005)
constant	0.0163	0.115***	0.00297	0.0174***
	(0.0105)	(0.00282)	(0.00447)	(0.00104)
Lender FE	No	Yes	No	Yes
N	149,883	149,883	149,883	149,883
R^2	0.072	0.074	0.029	0.026

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 8: Placebo: The Variant-Price Mechanism

Dep. Var.	% number of bids for plus loans		% amount invested for plus loans	
	(1)	(2)	(3)	(4)
$time$	0.00362	0.00274	0.00612	0.00598
	(0.00458)	(0.00550)	(0.00460)	(0.00553)
$time^2$	-0.00513***	-0.00486***	-0.00521***	-0.00494***
	(0.00032)	(0.00033)	(0.00032)	(0.00033)
$log(total\,investment)$	-0.0320***	-	-0.0293***	-
	(0.00190)		(0.00192)	
$bidding\,speed$	-0.00062***	-	-0.00069***	-
	(0.00014)		(0.00014)	
$HHI\,of\,investment$	-0.257***	-	-0.247***	-
	(0.0244)		(0.0245)	
$lender\,experience\,in\,months$	0.00155***	-	0.00154***	-
	(0.00011)		(0.00011)	
$time \times log(total\,investment)$	0.00618***	0.00599***	0.00582***	0.00553***
	(0.00044)	(0.00054)	(0.00044)	(0.00055)
$time \times bidding\,speed$	0.00008*	0.00008***	0.00009**	0.00009***
	(0.00003)	(0.00002)	(0.00003)	(0.00002)
$time \times HHI\,of\,investment$	0.0399***	0.0225	0.0388***	0.0187
	(0.00571)	(0.0128)	(0.00573)	(0.0129)
$time \times lender\,experience\,in\,months$	-0.00027***	-0.00025***	-0.00027***	-0.00024***
	(0.00002)	(0.00003)	(0.00002)	(0.00003)
$constant$	0.662***	0.478***	0.647***	0.482***
	(0.0170)	(0.00407)	(0.0172)	(0.00410)
Lender FE	No	Yes	No	Yes
N	75,790	75,790	75,790	75,790
R^2	0.013	0.011	0.012	0.010

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 1: A Loan Request Example on Prosper.com during the Single-Price Regime

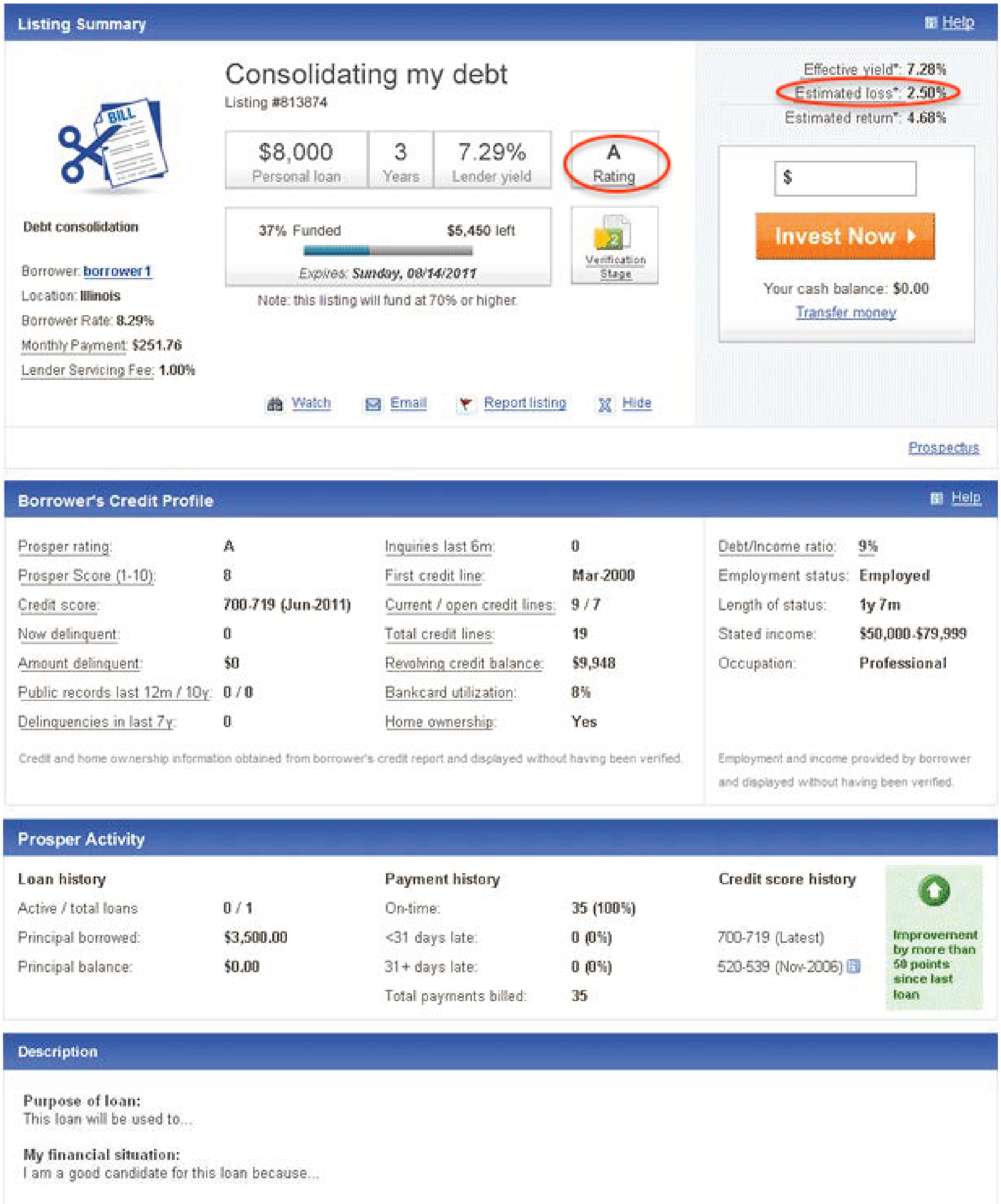


Figure 2: Interest Rates of the Loans Funded on Prosper.com over Time

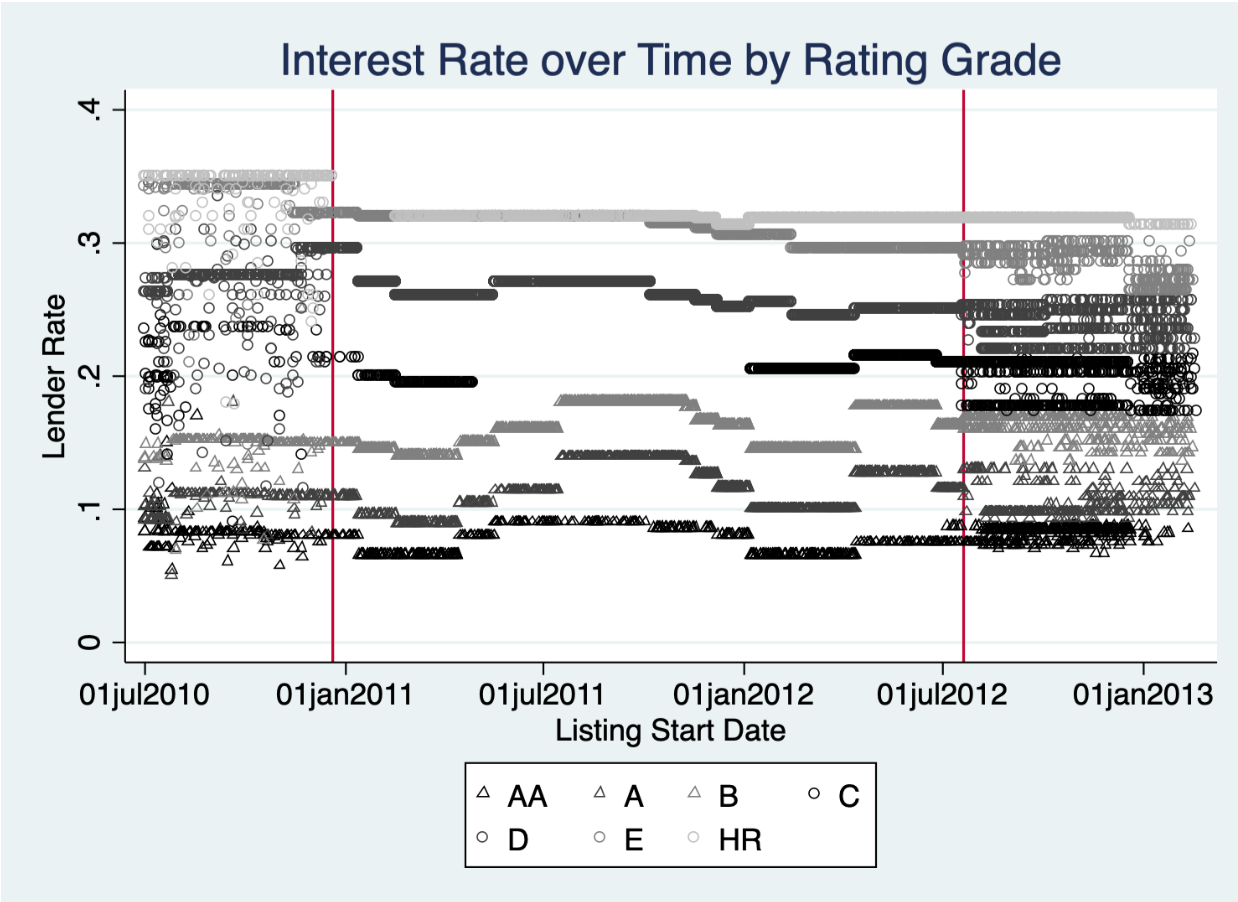


Figure 3: An Illustration of Platform Mispricing

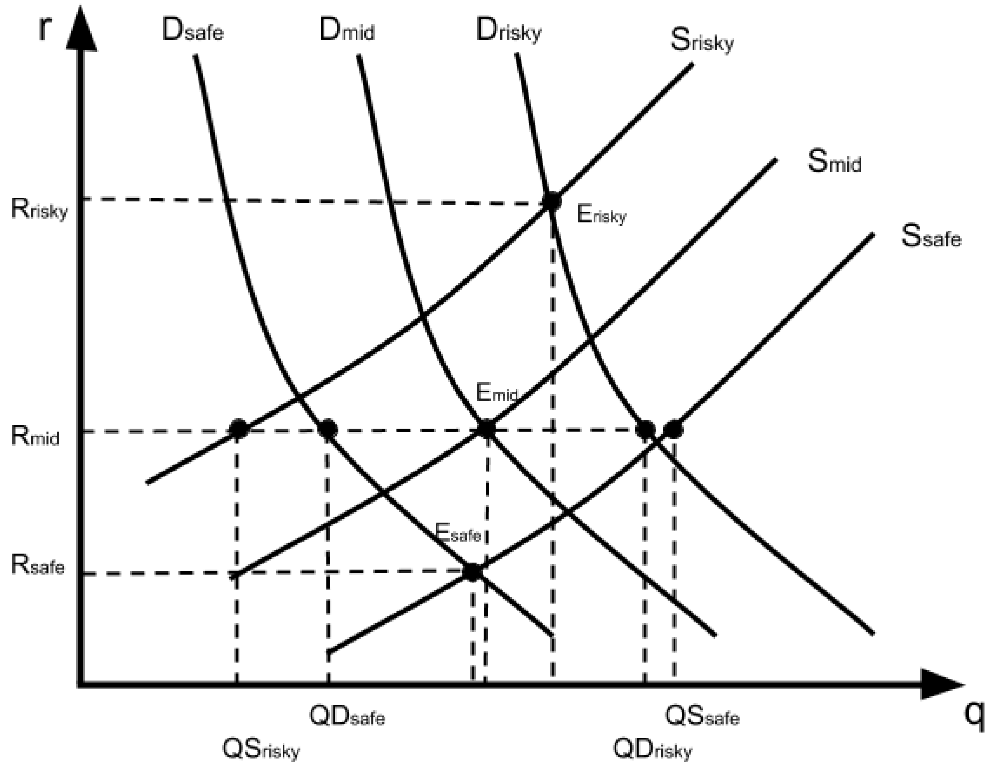


Figure 4: Distribution of Bidding Lag for Plus and Minus Loans under Different Pricing Schemes

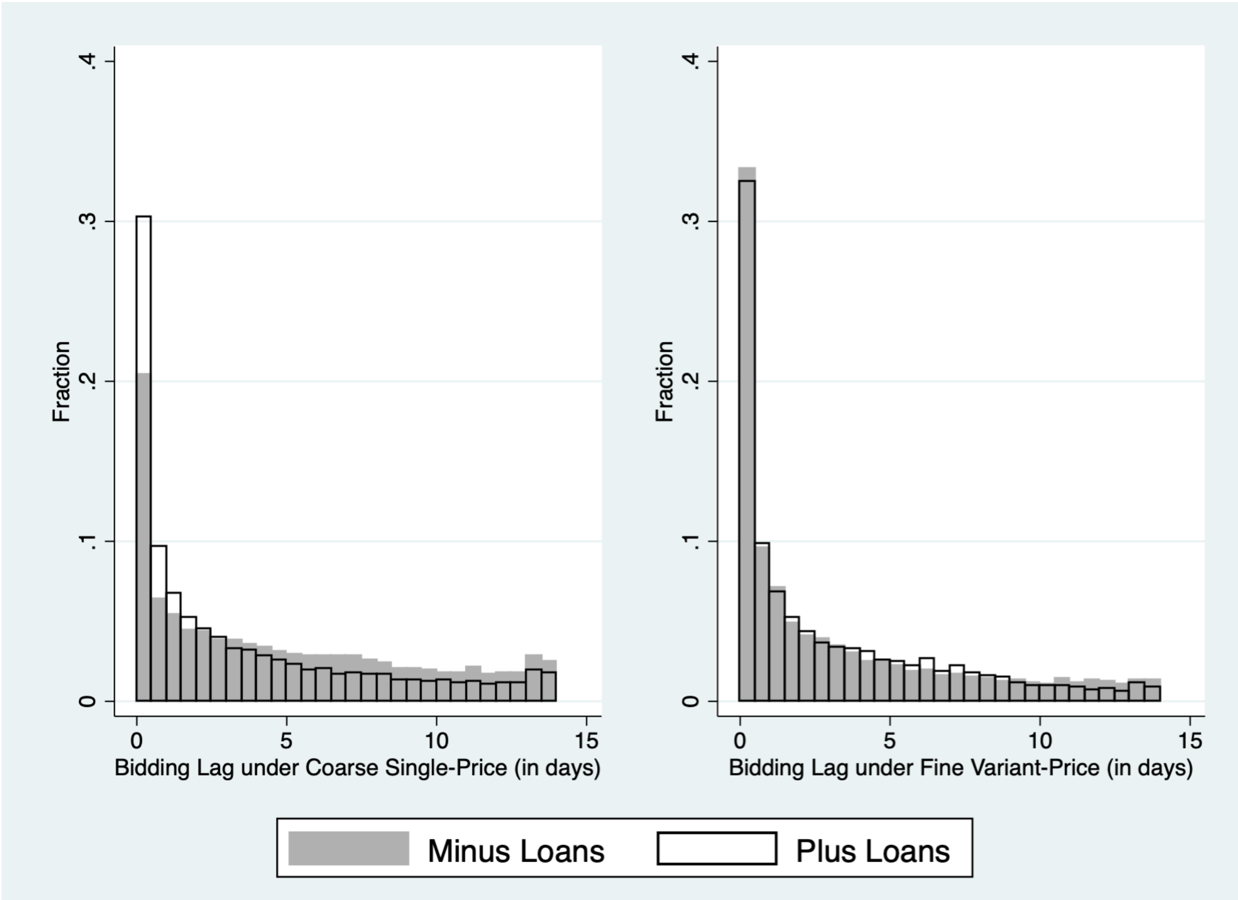
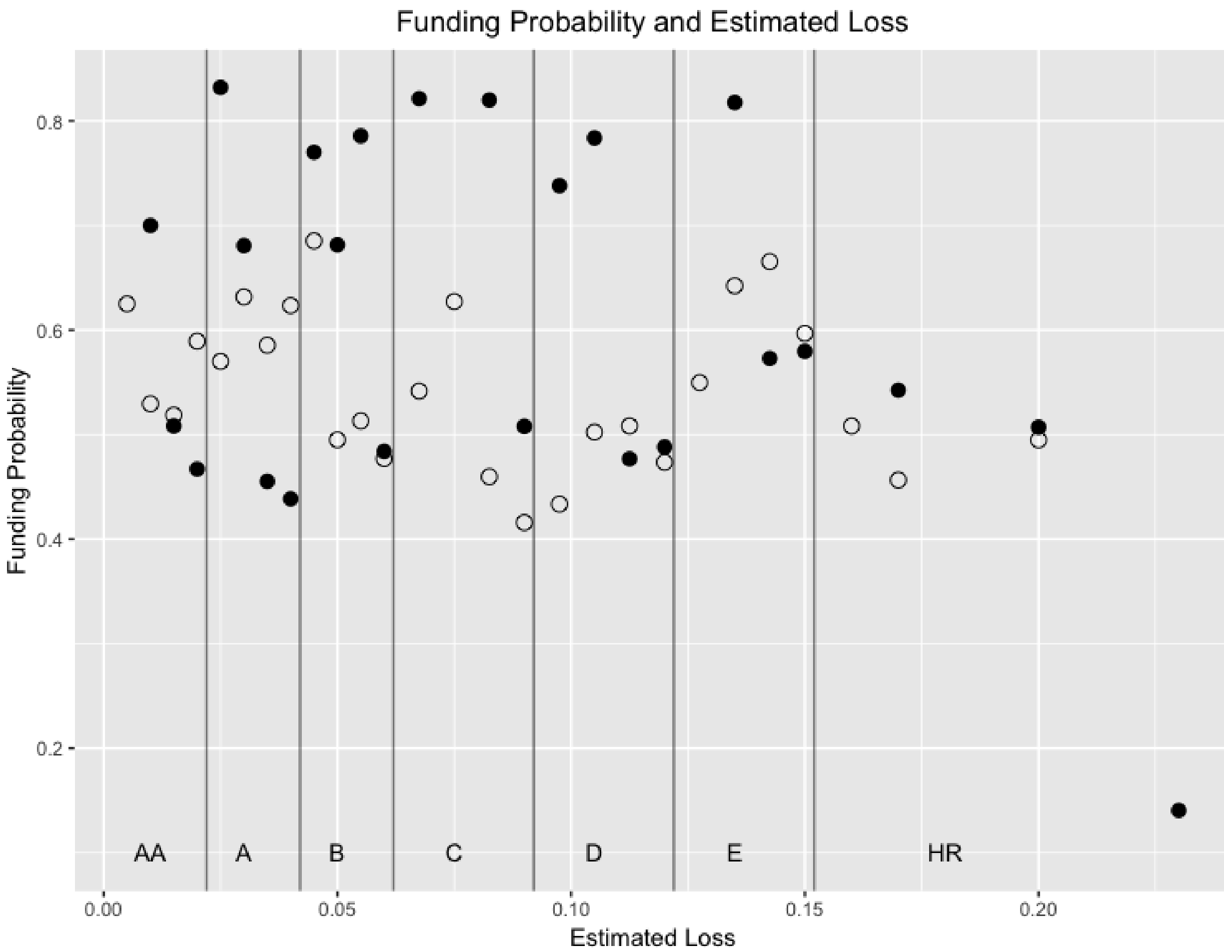
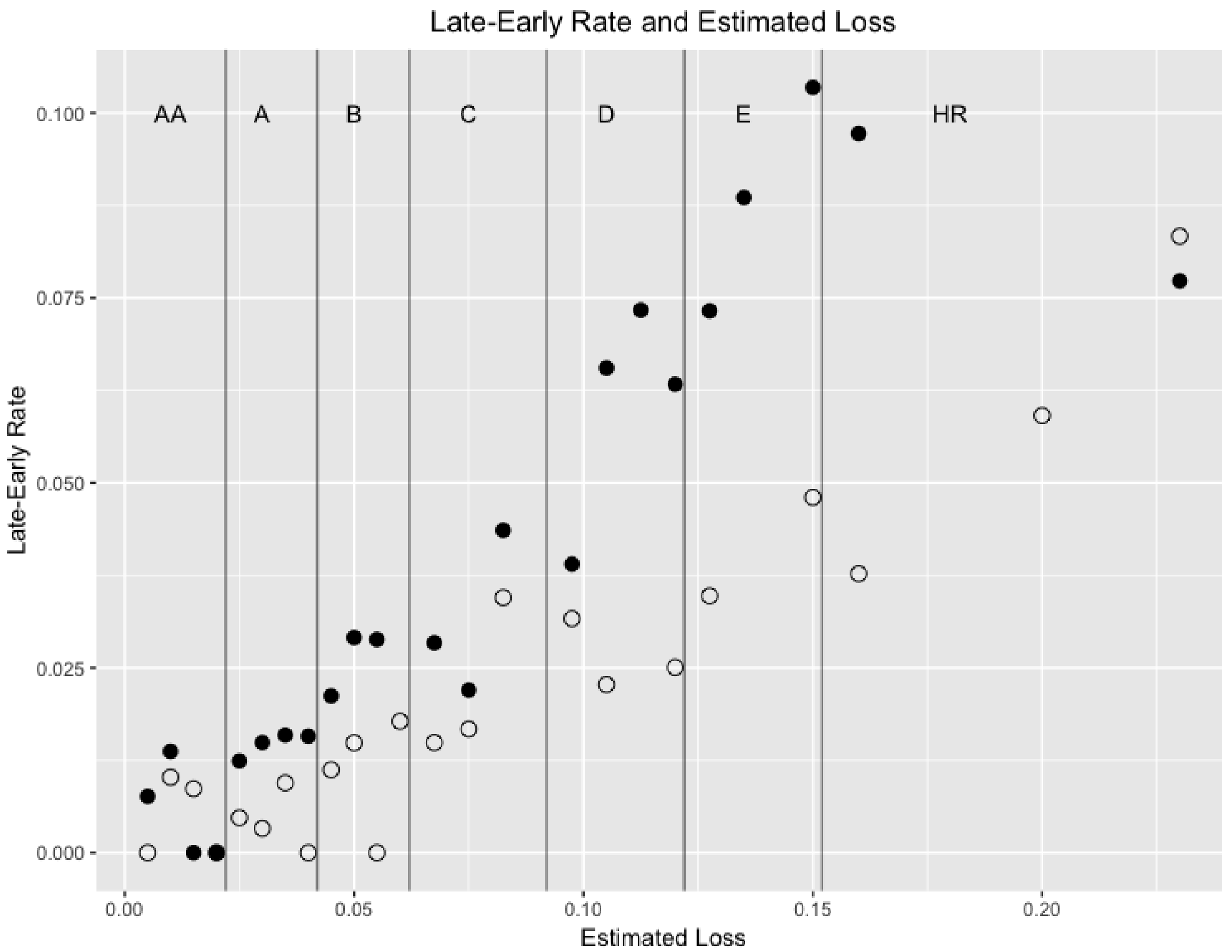


Figure 5: Funding Probabilities by Estimated Loss Rate within and across Prosper Ratings



Notes: The solid black dots and hollow black circles represent the funding probability of loan listings within bins defined by estimated loss during the coarse single-price regime and during the fine variant-price regime, respectively.

Figure 6: Late-Early Rate by Estimated Loss Rate within and across Prosper Ratings



Notes: The solid black dots and hollow black circles represent the delinquent-early rates of loans within bins defined by estimated loss during the coarse single-price regime and during the fine variant-price regime, respectively.

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Appendix

A Alternative Specifications

In this appendix, we report the results from several alternative specifications and regression techniques. First, in addition to the quadratic form of the time variable in the main specification, we also estimate the learning model with an alternative functional form of time. Here we report the results obtained using the logarithm of time. Table A1 and Table A2 show qualitatively similar results as in the main analysis. In another set of regressions, we run fractional logit regressions and two-sided Tobit regressions. The main coefficients are reported in Tables A3 – A6. Again, the results are not surprisingly consistent with the findings in our main specification.

Table A1: Log of Time Main Results: Baseline Regressions

Dep. Var.	% number of bids for plus loans		% amount invested for plus loans	
	(1)	(2)	(3)	(4)
$log(T)$	0.0350***	0.0342***	0.0360***	0.0352***
	(0.00143)	(0.00225)	(0.00143)	(0.00226)
$constant$	0.346***	0.348***	0.345***	0.347***
	(0.00340)	(0.00510)	(0.00341)	(0.00512)
N	149,884	149,884	149,884	149,884
R^2	0.004	0.004	0.005	0.005

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A2: Log of Time Results: Heterogeneity in Learning

Dep. Var.	% number of bids for plus loans		% amount invested for plus loans	
	(1)	(2)	(3)	(4)
$log(T)$	0.111***	0.119***	0.105***	0.110***
	(0.00961)	(0.0166)	(0.00968)	(0.0167)
$log(total\, investment)$	0.0521***	-	0.0506***	-
	(0.00261)		(0.00263)	
$bidding\, speed$	0.0000566	-	0.000109	-
	(0.00375)		(0.00378)	
$HHI\, of\, investment$	0.188***	-	0.182***	-
	(0.0323)		(0.0324)	
$is\, frequent\, lender$	0.00292	-	0.00464	-
	(0.00885)		(0.00889)	
$lender\, experience\, in\, months$	-0.00333***	-	-0.00334***	-
	(0.000187)		(0.000188)	
$time \times log(total\, investment)$	-0.0178***	-0.0175***	-0.0168***	-0.0163***
	(0.00109)	(0.00179)	(0.00110)	(0.00181)
$log(T) \times bidding\, speed$	0.00332*	-0.00207	0.00329*	-0.00259
	(0.00145)	(0.00338)	(0.00146)	(0.00363)
$log(T) \times HHI\, of\, investment$	-0.0671***	-0.168***	-0.0641***	-0.164***
	(0.0145)	(0.0435)	(0.0146)	(0.0436)
$log(T) \times frequent\, lender$	0.00614	-0.000815	0.00515	-0.00164
	(0.00366)	(0.00616)	(0.00368)	(0.00618)
$log(T) \times lender\, experience\, in\, months$	0.00121***	0.00122***	0.00121***	0.00124***
	(0.0000755)	(0.000124)	(0.0000759)	(0.000124)
$constant$	0.0984***	0.363***	0.108***	0.362***
	(0.0231)	(0.00527)	(0.0232)	(0.00529)
N	149,884	149,884	149,884	149,884
R^2	0.014	0.008	0.014	0.008

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A3: Main Results: Fractional Logit Regressions

Dep. Var.	% number of bids for plus loans		% amount invested for plus loans	
	(1)	(2)	(3)	(4)
time	0.0428***	0.1453***	0.0442***	0.1458***
	(0.0018)	(0.0077)	(0.0018)	(0.0078)
$time^2$		-0693***		-0.0687***
		(0.005)		(0.005)
N	149884	149884	149884	149884
Pseudo R^2	0.0016	0.0021	0.0017	0.0022

Marginal effects are reported at the population mean.

Delta method standard errors in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A4: Heterogeneous Learning Results: Fractional Logit Regressions

Dep. Var.	% number of bids for plus loans (1)	% amount invested for plus loans (2)
$time$	0.2284***	0.2198***
	(0.0148)	(0.0149)
$time^2$	-0.0506***	-0.0499***
	(0.0051)	(0.0051)
$log(total\, investment)$	0.2772***	0.2731***
	(0.0125)	(0.0126)
$bidding\, speed$	0.0002	0.0002
	(0.0003)	(0.0003)
$HHI\, of\, investment$	0.0088***	0.0087***
	(0.0013)	(0.0013)
$is\, frequent\, lender$	0.0082*	0.0086*
	(0.0037)	(0.0037)
$lender\, experience\, in\, months$	-0.1036***	-0.1041***
	(0.0050)	(0.0050)
$time \times log(total\, investment)$	-0.1861***	-0.1774***
	(0.0108)	(0.0109)
$time \times bidding\, speed$	0.0005	0.0005
	(0.0003)	(0.0003)
$time \times HHI\, of\, investment$	-0.0064***	-0.0062***
	(0.0012)	(0.0012)
$time \times frequent\, lender$	0.0020	0.0013
	(0.0030)	(0.0030)
$time \times lender\, experience\, in\, months$	0.0725***	0.0731***
	(0.0040)	(0.0040)
N	149884	149884
Pseudo R^2	0.0060	0.0062

Marginal effects reported at population mean.

Standard errors in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A5: Main Results: Two-sided Tobit Regressions

Dep. Var.	% number of bids for plus loans		% amount invested for plus loans	
	(1)	(2)	(3)	(4)
time	0.00820***	0.0261***	0.00837***	0.0261***
	(0.000320)	(0.00136)	(0.000320)	(0.00135)
$time^2$		-0.000886***		-0.000881***
		(0.0000643)		(0.0000641)
constant	0.290***	0.229***	0.289***	0.228***
	(0.00391)	(0.00618)	(0.00390)	(0.00617)
N	149884	149884	149884	149884
Pseudo R^2	0.0024	0.0030	0.0025	0.0031

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A6: Heterogeneous Learning Results: Two-sided Tobit Regressions

Dep. Var.	% number of bids for plus loans (1)	% amount invested for plus loans (2)
$time$	0.0390***	0.0381***
	(0.00260)	(0.00260)
$time^2$	-0.000627***	-0.000623***
	(0.0000651)	(0.0000650)
$log(total\,investment)$	0.0752***	0.0744***
	(0.00295)	(0.00295)
$bidding\,speed$	0.00452	0.00455
	(0.00542)	(0.00543)
$HHI\,of\,investment$	0.175***	0.172***
	(0.0466)	(0.0465)
$is\,frequent\,lender$	0.00395	0.00390
	(0.0104)	(0.0104)
$lender\,experience\,in\,months$	-0.00398***	-0.00397***
	(0.000206)	(0.000206)
$time \times log(total\,investment)$	-0.00400***	-0.00386***
	(0.000241)	(0.000241)
$time \times bidding\,speed$	0.000477	0.000475
	(0.000367)	(0.000368)
$time \times HHI\,of\,investment$	-0.0157***	-0.0153***
	(0.00418)	(0.00418)
$time \times frequent\,lender$	0.00111	0.00101
	(0.000825)	(0.000824)
$time \times lender\,experience\,in\,months$	0.000270***	0.000270***
	(0.0000161)	(0.0000161)
$constant$	-0.157***	-0.152***
	(0.0275)	(0.0275)
N	149884	149884
Psudo R^2		

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$