Risk-Based Pricing in Peer-to-Peer Lending*

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Abstract

We study the risk sensitivities of interest rates under auctions and posted prices in peer-to-peer lending. By exploring a pricing mechanism switch in an online lending platform, Prosper.com, we find that under posted prices, loan pricing is less sensitive to credit risk; the platform collects higher profits; lenders are less compensated for the credit risk taken, and borrowers experience less credit rationing. Analyses of repeat borrowers under both pricing regimes and tests with data under Prosper's upgraded posted prices confirm these findings. We argue that less risk-based pricing results from the incentive of the lending platform.

Keywords: risk-based pricing; peer-to-peer lending; credit risk; pricing regimes; auctions;

posted prices

JEL classification: D14, G13, G23, G51

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Introduction

A fundamental practice in any credit market is to compensate lenders with interest rates commensurate with the credit risk taken, which is known as risk-based pricing. In a competitive credit market with perfect information, the interest rate charged on loans should correctly reflect the borrower's credit risk, therefore leading to an efficient allocation of credit without credit rationing, as in Stiglitz and Weiss (1981). Although efficient risk-based pricing has long been a focus of research in traditional consumer credit markets such as mortgages, automobile loans, credit card loans and education loans (Adams et al., 2009; Duca and Rosenthal, 1993; Edelberg, 2006; Einav et al., 2012; Magri and Pico, 2011; Walke et al., 2018), few studies have conducted an in-depth examination of the risk sensitivities of interest rates in the online peer-to-peer lending market despite the growing academic interest in online credit marketplaces[1].

This paper sheds light on the pricing of credit risk in the online peer-to-peer lending market under alternative interest rate determination regimes. In particular, we examine whether and how the pricing of credit risk changes when Prosper.com, one of the largest online lending platforms for unsecured personal loans in the United States, changed its interest rate determination mechanisms from auction pricing to the posted price on December 20, 2010[2]. The abrupt change, unexpected by market participants, provides us with a testbed from which to identify the change in credit risk pricing[3].

[1] Peer-to-peer lending platforms, online credit marketplaces that match lenders and borrowers, have rapidly grown into a multibillion-dollar industry globally in recent years. For example, a recent study predicts that global peer-to-peer lending market may grow up to $897.85 billion by 2024 (source: "Peer-to-Peer Lending Market - Global Industry Analysis, Size, Share, Growth, Trends and Forecast 2016–2024", Transparency Market Research).

[2] The auction is a pricing regime that relies on the "wisdom" of the participating lenders and the relative strength of the borrowers and lenders to discover the prices of loans. Posted prices are the regime in which loan prices are predetermined by the platform as fixed interest rates. Borrowers and lenders can only choose to accept or reject. Section 1 provides more institutional details on each regime.

[3] The primary goal of the switch, as stated by Prosper, was to increase the transaction efficiency of deploying funds; that is, investors would be able to generate a higher turnover of assets, and borrowers could be funded sooner.

It is important to note that peer-to-peer lending platforms, as matchmakers in the market, bear much less credit risk than conventional lenders such as banks or credit market investors. The incentive mismatch can lead to inefficient management of the credit risk of platforms. According to SEC regulation, when platforms advertise estimated returns to investors, the only required disclosure is the calculation method.[4] In other words, platforms may originate loans of any quality at any rate without being transparent to investors. Furthermore, peer-to-peer lending is initially known to offer rates that are more attractive to borrowers than retail banks. Tang (2019) shows that borrowers migrate from banks to peer-to-peer lending platforms after they become unqualified for bank loans. It is unclear, however, whether peer-to-peer lending is set to attract more borrowers at the cost of investors.

Our study examines this issue from the perspective of risk-based pricing using Prosper's switch between two common pricing regimes in peer-to-peer lending. We propose a stylized model comparing a multiunit uniform price auction against the posted-price mechanism in peer-to-peer lending. The model yields the hypotheses that loan pricing is less sensitive to credit risk under the posted-price regime than under the auction regime; the profits of the platform under the posted-price regime are higher than in auctions; lenders earn lower returns under posted prices; and borrowers have a higher funding probability under the posted-price regime.

Our empirical analysis uses Prosper.com's transaction data, which include loan application (listings) terms, loan contract terms, loan performances, and borrowers' credit profiles. A major hurdle in the empirical analysis of risk-based pricing—the investigation of the sensitivity of the pricing of a loan concerning the loan's credit risk—is that the perceived credit risk of loans is not only subjective but also a piece of private information to lenders. Following the standard

[4] Paul Slattery, "Square Pegs in a Round Hole: SEC Regulation of Online Peer-to-Peer Lending and the CFPB Alternative", Yale Journal of Regulation, 2013

literature on credit-risk pricing (Edelberg, 2006; Magri and Pico, 2011), we assume that the fintech lending platform, equipped with both advanced analytics and complete information on borrowers' hard and soft information as well as on similar borrowers' historical loan performance, is likely to possess an unbiased credit risk estimator of borrowers upon loan origination. Hence, we develop the following two measures of borrowers' credit risk perceived by the lending platform.

First, using the sample borrowers' characteristics upon loan application as well as their *ex post* loan performance, we fit borrowers' probability of default before the loan maturity date using a pooled logit model as in Edelberg (2006) and Magri and Pico (2011). We then, from the fitted logit model, predict each borrower's probability of default before loan maturity.

Second, to capture the difference in the credit risks among borrowers who default at different times within their loan terms, we fit borrowers' time-inhomogeneous default hazard rate. The hazard rate allows us to predict each borrower's default time, as a loan that defaults later generates more coupon payments and is more valuable than its early defaulted counterpart.

We then test whether Prosper.com priced the credit risk differently under the two pricing regimes. Under both borrower credit risk measures, we find that the loan spread became less sensitive to the borrower's perceived credit riskiness after regime switching. In other words, the pricing of loans is less risk-based under the posted-price regime. To ensure that our results are not driven by new borrowers who entered the market after Prosper switched the regime to posted prices, we focus on the subsample of borrowers who received funding both before and after the regime switch. The result we obtain using the subsample remains consistent, suggesting that the lower sensitivity in risk-based pricing under the posted price is not due to sample selection bias.

To understand why Prosper.com adopted a regime switch leading to less risk-based pricing, we examine how such change affects borrowers, lenders and the platform. On the borrower side, we study the impact of pricing regime switching on funding decisions. We find that borrowers are less likely to be credit rationed under posted prices than under auctions and that the funding probability is higher among low-quality borrowers than among those with better credit ratings. Using single creditworthiness criteria under posted prices results in less credit rationing. We also find that funding decisions are less affected by loan pricing after Prosper switches its pricing mechanism to posted prices.

On the platform side, we estimate the sum of fees charged before and after the regime switch for Prosper.com, which profits mainly from the origination fees charged to borrowers and servicing fees charged to lenders. We find that profits increased significantly under posted prices. More importantly, the increase in profits primarily comes from high-risk loans.

Finally, on the lender side, we investigate the differential effect of the loan spread on lenders' P&L of investing and discover that lenders earn lower investment returns under posted prices. The evidence from the platform and lenders point to the possibility of moral hazard: the platform increased profits by choosing less risk-based pricing without bearing the associated loss. Even though our results suggest that the posted-pricing regime is inferior to auction pricing regarding pricing efficiency, funding probability increases under the less-efficient posted-price regime. We view investors' choice between auctions and the posted-pricing regime as a trade-off between competitive price discovery and convenience *à la* Einav et al. (2018). In other words, investors' increasing favor for less time-consuming posted prices is driven by a change in preference toward convenience. Investors' preference for a passive investment style also aligns with these trade-offs.

Our study contributes to the long-standing literature on risk-based pricing by investigating it in the context of emerging online peer-to-peer lending.[5] Adams et al. (2009), Edelberg (2006), Einav et al. (2012), Magri and Pico (2011), and Walke et al. (2018) empirically show that since the mid-1990s, various financial institutions have increasingly adopted risk-based pricing for different types of loans with risk premium spreads significantly rising over time for secured (e.g., mortgage loans) and some unsecured loans (e.g., credit card loans). Our work, which focuses on the online credit market, shows that the switch from auction to posted interest rates in the peer-to-peer lending platform leads to less risk-based pricing, contrary to what has been observed among traditional financial intermediaries. A thorough understanding of the pricing of risk in the online credit market has significant importance to both academic research and industry practice because P2P lending provides a substitute for bank lending in the underserved credit market (Tang, 2019).

This paper also connects to the broader literature on peer-to-peer lending and its market mechanism for interest rate determination.[6] Wei and Lin (2017) were among the first to study the different effects of auctions versus posted prices on transaction outcomes. They observe higher initial and contract interest rates, higher funding probabilities, and higher default rates for funded loans after the switch to posted prices on Prosper.com. While their study provides the first glimpse of an increased default rate for loans under posted prices, little is known about whether there is a systematic change in the pricing sensitivity of interest rates to default risk after the switch from auctions to posted prices. We fill this gap in the current research. In addition to the elevated borrower rates and higher funding probability for loans under the posted-price regime,

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[5] Chatterjee et al. (2007), Geanakoplos (2001), Livshits et al. (2011), and Riley (1987) developed theories about risk-based pricing.

[6] Recent studies include Balyuk and Davydenko (2019), Duarte et al. (2012), Emekter et al. (2015), Freedman and Jin (2017), Hertzberg et al. (2016), Hildebrand et al. (2017), Iyer et al.(2016), Lin et al. (2013), and Ramcharan and Crowe (2013).

as in Wei and Lin (2017), we find that the loan rates in the posted-price regime are less sensitive to borrowers' default risk. Our findings show that the higher default probability under the posted-price regime documented in Wei and Lin (2017) is due to the connections between weaker risk-based pricing and the lower qualities of borrowers in the posted-price regime. Compared to Balyuk and Davydenko (2019), who point out that the platform maximizes loan volume by retaining high-risk loans, we offer an alternative interpretation of the platform's strategy to increase loan origination by reducing risk-pricing sensitivity.[7]

Our findings on why P2P lending platforms prefer posted prices to auctions also speak to extensive literature comparing online auctions and posted prices. In particular, Einav et al. (2018) document a trend of the online retail market whereby sellers increasingly prefer posted prices, and Zeithammer and Liu (2006) find that eBay sellers with larger inventories prefer posted prices.[8] Our analysis explains why posted prices are preferred in the peer-to-peer lending context.

Finally, our findings of less risk-based pricing under posted price yield policy implication in view of some recent trends on the market. Balyuk and Davydenko (2019) find that institutional investors have provided over 90% of financing under passive investment management in the U.S. online credit marketplace. Valee and Zeng (2019) find that under a posted price, platform prescreening leaves room for further investor screening, and sophisticated investors may introduce adverse selection problems and systematically outperform less sophisticated investors. Thus, a less efficient pricing of credit risk under posted price may significantly increase the P2P market risk, calling for regulators' attention.

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[7] Ryan and Zhu (2018) document that a reduced incorporation of soft information lowers loan interest rates' predictability of default after a regime switch.

[8] In addition, Weeting (2012) observes that auction prices are typically below posted prices upon studying a Major League Baseball ticket resale. Hammond (2013) explored the explanation of the coexistence of auctions and posted prices in the online retail market.

The paper proceeds as follows. We provide more institutional details in Section 1 and motivate the empirical hypothesis through a stylized model in Section 2. After we describe the sample in Section 3, we demonstrate that the switch leads to less risk-based pricing in Section 4. We extend and discuss the results in Section 5 and conclude in Section 6.

1. Institutional Environment: Peer-to-Peer Lending Pricing Mechanisms

Auctions and posted prices are the most common pricing mechanism choices of peer-to-peer lending platforms. When Prosper.com was launched in 2005 as the first peer-to-peer lending platform in the U.S., Dutch auctions were chosen for loan pricing. When LendingClub.com, the largest peer-to-peer lending platform in the U.S., followed one year later, it began by using posted prices. However, Prosper.com unexpectedly dropped auctions and switched to posted prices on December 20, 2010. This policy change was primarily intended to simplify the loan allocation process and allow lenders to deploy funds with less hassle and time. This switch has also brought significant changes to the pricing of loans on Prosper.

When borrowers requested a loan on Prosper before the pricing mechanism switch, they would specify the requested loan amount, loan term, and maximum interest rate they were willing to accept.[9] The platform also asked borrowers to voluntarily provide information such as income, the purpose of the loan, employment status, and sometimes a picture from which lenders could evaluate borrowers' creditworthiness. In addition, Prosper would obtain the prospective borrower's credit report from a third-party credit report agency and use this, along with the borrower's supplied information and borrowing history on the platform, to assign a proprietary internal credit rating to the loan application and provide it to lenders for reference. The rating

[9] The maximum interest rate a borrower can post is capped at 36%.

had seven ranks: AA, A, B, C, D, E, and HR, with AA denoting the lowest risk level and HR being the highest. Prosper also sets the minimum interest rate for each rating.

Once a borrower completes a loan request, Prosper creates a listing containing all the information and provides it to lenders for bidding.[10] Then, Prosper conducts a multiunit uniform-price auction. For each bid, lenders specify the amount of funds and the minimum interest rate they are willing to lend. Lenders who bid on the listing are ranked by the interest rate they post for their bid. Once the bidding amount exceeds the requested loan amount, Prosper sets the interest rate of the loan as the highest interest rate posted by lenders who can fund the loan. The lenders who bid with interest rates equal to or lower than this rate are able to fund the loan. Each listing has a bidding period, typically of seven days. If a listing does not receive a bidding amount of more than or at least equal to the requested loan amount during the period, the listing expires without being funded. To conclude, under the auction-pricing regime, the loan interest rate is initially posted by a borrower within the band set by Prosper and is discovered by the "wisdom of the crowd" among lenders.

Under posted prices, Prosper assigns an interest rate to each listing based on Prosper's internal credit rating as well as other factors, such as loan terms, group affiliations, and the general economic environment[11]. Unlike the auction regime in which each loan has a tailored interest rate discovered by lenders, under the posted-price regime, there are only fixed interest rate levels, mainly corresponding to Prosper's internal credit rating. Lenders can still decide whether to fund a loan and how much funding to contribute by evaluating the creditworthiness of borrowers, but they cannot determine the interest rate. Loans are either funded at the preset interest rate or canceled if there is not sufficient funding. Prosper also made a few other changes

[10] Appendix D shows an example of an online listing.

[11] This is described in Prosper's POS AM filing on December 17, 2010.

at the time of the regime switch. Partial funding became permissible if a loan received 70% of the requested amount. The funding time was extended to fourteen days instead of seven days, and the bidding on a loan was set to terminate as soon as the loan received sufficient bids.

2. A Model of Pricing Regimes and Hypothesis Development

We present a stylized model of the motivation for Prosper's switch in pricing regimes from auctioning to posted pricing. We argue that Prosper made such a switch to increase the loan funding probability and the profits the platform can collect from the loan origination.[12]

Motivated by the actual funding procedure, we set the example of a borrower seeking a P2P loan who demands I units of capital and is willing to pay a maximum interest rate $\bar{R}$ for the loan. We also have N lenders in the economy, indexed by $i \in \{1, \ldots, N\}$, where each funds one unit of capital in the loan rather than multiple units.[13] Each lender i analyzes the background information of the loan provided by the P2P platform and determines fair interest rate r_i.[14] Interest rate r_i across lenders for borrower A follows a distribution with cumulative distribution $F^A(r)$. Moreover, if borrower A is riskier than borrower B, we have $F^B(r) > F^A(r)$.

Under auction, each of the lenders strategically submits the level of interest rate p_i at which he is willing to lend his unit of capital, so p_i may not be the same as his break-even interest rate r_i. After lenders submit their lending rates p_i for all i, Prosper, the platform, aggregates all the submissions and funds the loan using the I submissions with the lowest interest rates. Prosper specifies the lowest Ith rate as the realized loan rate R. The realized loan rate R can only be

[12] Gonsalves, Atone. "Social Lender Prosper.com Drops Auction Model." InformationWeek, December 20, 2010.
[13] In fact, by investing in only one unit of capital to a borrower, a risk-averse lender can diversify his investment across as many borrowers as possible and therefore increase the utility gain from lending out a given amount of capital. We choose not to specifically model the lender's diversification since it does not directly relate to Prosper's choice between the auction and posted price regimes but let each lender invest in only one unit of capital.
[14] In other words, if the lending rate is r_i, the lender breaks even and obtains a zero expected payoff.

lower than $\bar{R}$, in which case the borrower obtains the funding requested. Otherwise, the loan does not originate, and the borrower receives no funding from any lenders. Conditional on the successful origination of a loan, Prosper charges a servicing fee equal to a fraction s of the I units of capital requested.

On the other hand, under the posted price, Prosper can directly choose loan rate $R' \leq \bar{R}$ such that R' is the lowest rate that can attract at least I lenders with $r_i \leq R'$. The lowest rate allows Prosper to attract as many borrowers as possible.

We now show the following proposition:

Proposition 1. Loan risk pricing is more sensitive to borrower risks under the auction mechanism than under the posted-price mechanism. Furthermore, the funding probability is lower under auctions than under the posted-price regime.

The proof of Proposition 1 is relegated to Appendix A. Proposition 1 suggests our first hypothesis as follows:

Hypothesis 1. Conditional on loans being funded, loan pricing is less sensitive to credit risk under the posted-price regime than under the auction regime.

In addition to loan pricing, we are also interested in comparing the funding probabilities of loans under auction and posted pricing. Our proposition predicts that the funding probability is higher under the posted-price regime than in auctions. Since the P2P platform charges servicing fees on each funded loan, the funding probability also links to the total servicing revenue of the P2P lender. The proposition also directly leads to the following hypothesis with regard to the lending platforms and the lenders:

Hypothesis 2. Conditional on loans being funded, the sum of fees collected from borrowers and lenders under the posted-price regime is higher than that of auctions.

Although the posted-price regime generates a higher funding probability, its impact on lenders' investment returns depends not only on how often the loans are funded but also on how the funded loans are repaid. If the posted prices are less sensitive to credit risk, lenders are expected to be compensated less for the risk taken. This leads to our third hypothesis:

Hypothesis 3. Conditional on loans being funded, lenders are compensated less for the credit risk taken under the posted-price regime than under the auction regime.

3. Data and Descriptive Evidence

We exploit a proprietary dataset showing both the listing and performance information of P2P loans originating on Prosper.com for the period of December 1, 2009 -- December 31, 2011, marking one year before and one year after the regime switch month, respectively. Notwithstanding the unanticipated regime switch, we choose to exclude the loans originating during the month of the regime switch from December 1, 2010 to December 31, 2010 to minimize the impact of selection bias. We focus on three-year loan listings, which account for 95% of all listings, and the subsequently funded three-year loans.[15] This gives us 37,335 listings and 13,380 loans originating within our sample period, and the loan performance data for this study end on December 31, 2014.[16]

Our primary interest is in the impact of the loan origination regime switching on risk-based pricing. Since the announcement may have impacted borrowers' and lenders' behaviors at the

[15] The rest of the 5% loan applications are one-year and five-year listings. Our results remain qualitatively the same with the inclusion of one-year and five-year loans.
[16] Since we obtained the sample data in July 2018, our sample contains the complete loan performance information from origination to maturity.

time, we exclude loans requested in December 2010.[17] Moreover, during the selected sample period, the regime switch was the only major policy change on the platform.[18] Therefore, the difference between the first half of the sample (December 1, 2009 – November 30, 2010) and the second half of the sample (January 1, 2011 – December 31, 2011) allows us to study the impact of regime switching on P2P risk pricing.

Table 1 summarizes the main sample of loan listings. It consists of 37,335 loan listings, of which 13,380 became loans, with 4,902 funded under auctions and 8,478 funded under posted prices. For each loan listing, we obtain the requested amount, interest rate, loan term, loan origination date, funding start and end times, loan status (fully paid, late, charged-off, or bankruptcy), and repayments made on each payment cycle. For borrowers who requested loans, we obtain their credit profiles, including credit ratings, debt-to-income ratios, lengths of credit history, amounts delinquent, bankcard utilization, current credit lines, homeownership, investment group membership, etc. Among the funded loans, we observe that the average interest rate charged on loans is 22%. The average score of Experian ScoreX is 705, and the average size of a typical loan is $5,789. By examining the characteristics of successful borrowers, we see that the mean monthly income of borrowers on Prosper is $5,600, with a mean debt-to-income ratio of 0.23. On average, a successful borrower has 9.59 open credit lines, carries a $19,722 average revolving credit balance, and has made 1.14 credit inquiries within the six-month window prior to the loan origination.

[17] Prosper announced its decision to switch one week before the switch date, December 20, 2020. During this week, for example, some lenders may have delayed their bidding until the posted-price mechanism was implemented since they envisioned that their funds would be deployed faster under the posted-price regime. This may, in turn, have affected loan pricing in auctions.

[18] Prosper.com also extends the funding duration from 7 days to 14 days. Wei and Lin (2017) have shown that funding duration does not explain increased funding probability under posted prices.

Prosper.com, after the regime switch, not only funded more loans (4,902 under auctions versus 8,478 under posted prices) but also attracted more high-risk borrowers. The latter is evident from Prosper's in-house ranking of borrower riskiness. Figure 1 plots the amount of loans funded (Panel A) and their percentages (Panel B) under both auctions and posted prices across all seven borrower credit grades from AA to HR. Clearly, the loan amount funded for borrowers with lower credit ratings has increased under posted prices. Table 2 further reports the loan distribution by credit rating before and after the regime switch. Except for loans with AA ratings, there is an increase in both the amount and the number of loans funded in all other ratings after the regime switch. The most significant increase in the number of loans funded under the posted-price regime occurs for loans with the "E" rating, which increase by 333.96%. For all loans funded during the sample period, loans with a "D" rating represent the most loans funded, accounting for 26.96% of the total number of loans provided. The majority of loans with a "D" rating also originate after the regime switch, with the number of loans funded more than doubling and the amount of loans funded more than tripling under the posted-price regime. Loans with "D", "E" and "HR" ratings account for 60.59% of the total number of loans funded after the regime switch. Therefore, the loan distribution after the regime switch is clearly tilted toward riskier ratings.

We next turn to the summary statistics of loan performance. Panel A of Figure 2 shows that loans funded under posted prices are more likely to be charged off, late in payment, and file bankruptcy. Panel B of Figure 2 suggests that the average loan spread tends to be smaller under posted prices for C, D, E, and HR ratings. Table 3 summarizes the loan status distribution. Overall, default loans account for 22.47% of the total number of loans, with total principal losses of approximately $8.02 million. Another 5.57% of funded loans, which constitute approximately

$4.08 million, could have been lost since the borrowers were more than 30 days late in making payments. Approximately 77.53% of the loans were fully paid, with an approximate value of $61.57 million. There is a significantly increased percentage of default loans after the regime switch, with 18.12% defaulting under auctions and 24.99% defaulting under posted prices, which also results in dramatic principal loss increases from $1.96 million under auctions to $6.06 million under posted prices.

4. The Link Between Loan Spreads and Credit Risk

In this section, we investigate whether loan pricing sensitivity to credit risk changes after the regime switch. To examine how Prosper determines loan spreads given the borrower's loan application profile, we follow the standard two-step process used in the risk-pricing literature (Edelberg, 2006; Magri and Pico, 2011). First, in subsection 4.1, we estimate each borrower's probability of default as the measure of credit risk. Next, in subsection 4.2, we investigate the loan spreads given the borrower's estimated credit risk and study how regime switching affects the spreads. We also show the robustness of our empirical results under both the Cox hazard rate estimates of default probability (subsection 4.3) and alternative approaches of sample construction (subsection 4.4).

4.1 Estimation of the probability of default

We estimate the probability of default using a logit regression with the actual default indicator set as the dependent variable. We include all of the borrower credit characteristics available to lenders in the estimation of the borrowers' probability of default. Some of the variables are forms of borrower self-reported credit information, such as homeownership, employment status, and stated monthly income. Variables are also pulled from Experian, a third-party credit report agency, including borrowers' bankcard utilization, current credit lines, current delinquencies and ScoreX scores. We include the Prosper rating in our estimation of default risk because it is one of the indicators available to investors to assess the default risk of loans.[19]

We also account for one unique credit characteristic of peer-to-peer lending loans when we measure borrowers' credit risk: social networking between peer borrowers and lenders on the platform. At Prosper, borrowers and lenders can choose to join self-created investment groups. These networks can be seen as an attempt to overcome information asymmetry problems in the credit market, thus potentially providing opportunities for lenders to become informed about the unobservable credit risk of borrowers through social network connections (Morse, 2015). Many peer-to-peer lending studies show that social networks affect borrowers' probability of default, loan pricing, and lenders' profitability (Everett, 2015; Freedman and Jin, 2017; Hildebrand et al., 2017; Lin et al., 2013). Therefore, borrower group membership status is included as an explanatory variable when estimating a borrower's credit risk.

The structure of the data allows the probability of default to be estimated with a binary logit regression. First, we define defaulted loans as loans that are charged off, have filed bankruptcy, and are more than 30 days late in payment. The loan default status is transformed to a default indicator with 1 indicating a defaulted loan and 0 denoting otherwise. We run binary logit regressions with the loan default indicator set as the dependent variable and borrower credit characteristics set as explanatory variables. We then use the coefficients from the logit regression

[19] Prosper assigns a rating based on its estimated loss rate (ELR) of each loan. Balyuk and Davydenko (2019) points out that when they predict variations in default risk using borrower characteristics, many variables are significantly related to the default hazard even after controlling for the ELR. Thus, we include the Prosper rating in our estimation of default risk, and our findings are also consistent with Balyuk and Davydenko (2019).

to predict the probability of default for each funded loan. We transform the likelihood of default into a continuous number of zero to one with the following model:

$$p_i = Pr\,\{Actual\ Default_i = 1\}\,, \qquad (1)$$

where p_i is the predicted probability of default of funded loan i. Following the properties of logistic regression, we further assume that n independent variables are linearly related to the log-odds:

$$\ln\,[p_i/\,(1 - p_i)] = b_0 + b_1 x_{i1} + b_2 x_{i2} + \cdots + b_n x_{in} + \varepsilon_i, \qquad (2)$$

where x_i are the independent variables and n is the number of covariates. We use the predicted value of the probability of default p_i as a measure of credit risk in the interest rate estimation in the following section.

The result of the estimation is reported in the first column of Table 4. Of the eighteen variables included in the binary regression model, eight significantly affected the outcome of loans at the 1% level. Borrowers are more likely to default when they have more current delinquencies, more inquiries and longer credit histories. Meanwhile, borrowers are less likely to default if they are Prosper group members, have higher credit scores, have higher bank card utilization, or have more credit lines. By using the coefficients of the estimation, we obtain a predicted probability of default for each funded loan as a proxy for credit risk[20].

In the logit estimations of credit risk, the sample used in the estimation consists of only funded loans, which could be nonrandom. Therefore, the regression results may be biased due to sample selection. Following Rosenbaum and Rubin (1983), we use an inverse propensity score weighted logit regression to mitigate the selection bias. To be consistent, we use the same set of

[20] The predicted probability of default is also measured by unweighted and inverse propensity score weighted probit regressions. The estimation produces consistent results. For brevity, the results are not reported but are available upon request.

variables of borrower characteristics from the previous unweighted logit regression. The estimation result is reported in the second column of Table 4. The coefficients are very similar to the estimation in column (1). The average probabilities of default estimated by unweighted and inverse propensity score weighted logit regression are 22.47% and 22.64%, respectively. Figure 3 plots the density of both distributions with Panel A focused on unweighted logit estimation and Panel B focused on inverse propensity score weighted logit estimation.

4.2 Analyses of loan spread sensitivity to credit risk

The empirical strategy for analyzing loan spread sensitivity to credit risk before and after the regime switch is to interact a postswitch indicator with the estimated credit risk to examine the differential effects of the perceived credit risk on the loan spread. The dependent variable, loan spread, is calculated as the borrower's interest rate minus the corresponding one-year daily treasury rate. The explanatory variables are the postswitch indicator, the estimated credit risk, and the interaction term of the postswitch indicator and estimated credit risk. We control for the loan amount and variables of the macroeconomic environment, which include Housing Price Index and unemployment rate Analytically, we test

$$\begin{aligned} Loan\ Spread_i = \ & \beta_0 + \beta_1 Postswitch_i + \beta_2 Estimated\ credit\ risk_i \\ & + \beta_3 Postswitch_i \times Estimated\ credit\ risk_i + \beta_4 Loan\ amount_i \\ & + Macroeconomic\ environment\ controls + \varepsilon_i \ . \qquad (3) \end{aligned}$$

The key variable of interest is the coefficient of the interaction term between the estimated level of credit risk and the postswitch indicator, which captures the differential effect of loan pricing sensitivity to credit risk between auctions and posted prices. Table 5 reports the OLS regression results of model (3). We report two models using the predicted probabilities of default obtained from both unweighted (in column 1) and inverse propensity score weighted (in column 3) logit regressions.[21] The negative coefficient of the interaction term suggests that the loan spreads after the regime switch are less sensitive to credit risk. The effect of borrowers' credit risk on loan pricing decreases statistically and economically after the switch. We also see that borrowers' credit risk, as measured by the predicted probability of default, has a positive and significant impact on the loan interest rate. For the other explanatory variables, larger loan sizes are correlated with a lower interest rate, Of the macroeconomic control variables, higher housing price indices (HPI) are associated with a higher interest rate[22].

To verify whether the borrower characteristics in the estimation of the probability of default have residual explanatory power for the loan spreads, we examine the estimation of loan spreads while adding all borrower creditworthiness characteristics as explanatory variables in addition to the variables used in the previous analyses. The results of the estimation with all variables are reported in column (2) for unweighted regression and in column (4) for inverse propensity score weighted regression. The key coefficient of the interaction term remains negative and significant, but at a smaller magnitude, after taking into account all variables of borrower characteristics. The pattern of decreased risk-based pricing after the regime switch is still evident.

In Figure 4, we plot the interest rate against predicted default risk for pre- and postswitch loans. For each loan, the loan spread is predicted by the estimated probability of default, while other significant variables are set to their mean values for the whole sample period in the model. Under unweighted logit regression, the slopes for the predicted interest rate against default risks

[21] To address the concern that Prosper.com's regime switching decision might relate to the borrower's default probability, we provide an alternative estimation of the probability of default in Appendix C.1. Specifically, we estimate the default probability using only the performance of loans funded under auctions (from December 1, 2009 to November 30, 2010). Table C.1 presents the estimate of our baseline model (3) using the alternative default probability, and shows that the empirical results remain consistent with Table 5.

[22] As an alternative to macroeconomic controls, we also control for time fixed effects (month) and ScoreX bin fixed effects in this and subsequent analyses. Although the sample size becomes smaller, the significance of results remains the same. The results are not reported for brevity, but available upon request.

are 0.761 and 0.559 for pre- and postswitch loans, respectively. This means that with an increase of 1% in default risk, the loan spread increases by 76 basis points prior to the switch but only increases by 56 basis points after the switch. The slopes become 0.749 and 0.556 for pre- and postswitch loans, and a 75 versus 56 basis points increase, respectively, for a 1% increase in default risk. Consistent with the results in Table 5, the slopes are steeper in the preswitch period than in the postswitch period, indicating that the default risk premium decreases after the switch.

4.3 Cox proportional hazard model

We have thus far shown that after Prosper switched to a posted price, the loan spreads became less sensitive to a borrower's probability of default, which we estimated using a logit model. One might be concerned about the limitation of the logit model in capturing the time-varying hazard ratio of default. To address this concern, we measure credit risk through a survival analysis of a loan's time-to-default by utilizing a Cox proportional hazard model (Cox, 1972) in this subsection. The model can be expressed as

$$h_i(t) = [h_0(t)]\exp(b_0 + b_1x_{i1} + b_2x_{i2} + \dots + b_nx_{in}), \qquad (4)$$

where h(t) is the hazard rate at time t; in the model, this reflects the likelihood that a loan will default at time t. The hazard rate measures the riskiness of individual borrowers inferred by the performance of all other borrowers with similar profiles. $h_0(t)$ is the baseline hazard rate at time t. x_i denotes the variables of borrower characteristics included in model (1).[23] The dependent variable is the number of months passed from the origination date of the loan to the default date if the loan defaults. The default date is replaced with the maturity date if the loan is fully paid off.

[23] We choose not to include fixed effects in the Cox proportional hazard model as Allison (2009) has shown that the fixed effects lead to biased Cox hazard rate estimates.

We graph cumulative baseline default rate function $h_0(t)$ in Figure 5. The figure shows that the cumulative baseline hazard increases as the loan age increases.

The results of the Cox proportional hazard model are presented in Table C.2 of Appendix C. We report both coefficients and hazard rates. According to the loan's internal rating, the hazard rate increases from 2.88 to 4.17, 4.24, 6.41, and 7.97 from ratings A to E, respectively, and lowers to 7.24 for rating HR. This indicates that borrowers in rating categories A, B, C, D, E, and HR are respectively 2.88 to 4.17, 4.24, 6.41, 7.97, and 7.24 times more likely to default than borrowers with the lowest risk rating of AA.

We then reexamine the loan spread sensitivity to credit risk before and after the regime switch using loans' time-to-default in various default months. We first estimate the hazard rate using model (4) at the 24th and 36th months and then replace the estimated credit risk in model (3) with hazard rates and rerun model (3). The results of the regressions are reported in Table 6. The results are highly consistent with the results shown in Table 5. The hazard rates of default in the 24th and 36th months are positively significant in explaining the loan interest rates. The coefficients of the interaction terms of the postswitch indicator and the hazard rate of default for the 24th and 36th months are negative and significant, which indicates that loan spread sensitivity to credit risk, as measured by the Cox proportional hazard model, decreases after the regime switch. At the 24^{th} and 36^{th} months, if the expected number of events of default increases by 1%, the interest rate will increase by 35.9 and 36.6 basis points prior to the switch, respectively, while it will increase by only 35.1 and 34.6 basis points, respectively, after the switch. Taken together, our findings indicate that loan pricing is less sensitive to credit risk under posted pricing.

4.4 Subsample of repeat borrowers

Another concern is that our results may be driven by changes in the borrower composition after Prosper changed its pricing regime. Tang (2019) notes that borrowers were seeking peer-to-peer lending loans after banks tightened credit supplies in 2011 due to the implementation of the new FASB regulation to consolidate off-balance sheet assets. The time frame of the implementation of the regulation, which started in the first quarter of 2011, overlaps with that of the pricing regime change of Prosper. Changes in borrower composition after the regime switch can introduce endogeneity and bias our results. To address this issue, we select a subsample of repeat borrowers who requested loans before and after the regime switch during the sample period. The subsample consists of 5,666 loan listings and 3,012 funded loans. We run the regression of model (3) using the subsample of funded loans, and the results are reported in Table 7. Notably, the coefficient of the probability of default is 1.016, whereas the coefficient of interaction of the postswitch dummy and the probability of default is -0.509, and both are statistically significant at the 1% level. For the subsample of repeat borrowers, the loan spread increases by 101.6 basis points for a 1% increase in the probability of default under auctions. However, the loan spread only increases by 50.7 basis points after the switch to posted prices. This evidence strongly suggests that a change in borrower composition is unlikely to affect our findings. Overall, our results support Hypothesis 1.

5. Extensions and Discussion

After showing the significant change in risk-based pricing after the regime switch, we now further investigate how such a change affects borrowers, the lending platform, and lenders. As a final robustness check, we also use the ex post loan performance information to verify whether our conclusion holds when we use realized default events rather than the estimated probability of default.

5.1 Impact on borrowers

To observe lower risk-based pricing's impact on the availability of credit (credit rationing) to borrowers, we examine the funding probability before and after the pricing regime switch. The stylized model predicts that the funding probability under auction is lower than that under the posted-price regime. We construct a linear probability model to test this prediction. The logit regression specifications are as follows:

$$Funding\ indicator_i = \beta_0 + \beta_1 Postswitch_i + Listing\ characteristics\ controls + Macroeconomic\ environment\ controls + \varepsilon_i. \qquad (5)$$

The funding indicator equals one if a listing is funded and equals zero if a listing does not receive funding. The regression results are reported in Table 8. Panel A reports the pooled logit regression result. Panels B and C show the results of inverse propensity weighted logit regression and unweighted logit regression using the subsample of repeat borrowers, respectively. Among all listings in the sample, funding probability appears to have largely increased after the pricing mechanism switch. For example, for all listings, the coefficient of the postswitch dummy is 1.076 and is statistically significant at 1%. This suggests that while holding other control variables constant, the odds ratio in which the odds of funding probability under posted price is divided by the odds of funding probability under auctions is 2.93, which is the natural exponential of 1.076. The empirical result is consistent with the model prediction that borrowers are less likely to be credit rationed under posted prices than under auctions. We also analyze funding decisions based on heterogeneity in borrower credit quality. If less risk-based pricing does indeed affect credit availability, then the estimates should be larger among borrowers with poor credit quality. The results in columns 2 to 8 are separate estimates of the probability model for the seven different credit grades. Among the lower quality borrowers – those rated "C", "D", "E", and "HR" – there is a higher funding probability under the posted-price regime than under the auction price. The magnitude also appears to be economically large. For example, while the coefficient of the postswitch dummy for credit rating category 'AA' is not significant, it is 1.405 and statistically significant at the 1% level for credit rating category 'E', suggesting that while holding other variables constant, the odds ratio (the odds of funding probability under a posted price divided by the odds of funding probability under auctions) is 4.076, the natural exponential of 1.405, for low credit rating category 'E'. The results from the inverse propensity score weighted logit regression (Panel B) and the subsample of repeat borrowers (Pane C) show consistent patterns.

We also examine the relationship between funding decisions and loan pricing. As we observe that borrowers with maximum interest rates are willing to pay under auctions and assigned interest rates of loan applications under a posted-price regime when they do not receive funding, we construct three interest rate spreads (borrower side): 1) for unfunded loans under auctions, it is the maximum interest rate under auctions minus the corresponding daily treasury rate; 2) for unfunded loans under posted price, it is the assigned interest rate minus the corresponding daily treasury rate; 3) for funded loans, it is the contract interest rate minus the corresponding daily treasury rate. To test the impact of loan pricing on funding decisions before and after the regime switch, we estimate a logit regression with the funding indicator set as the dependent variable and the postswitch indicator, interest rate spread, and interaction term of the postswitch indicator and the interest rate spread as explanatory variables. We control for borrower credit characteristics, the listing amount, and the macroeconomic environment. The regression specifications are as follows:

$$Funding\ indicator_i = \beta_0 + \beta_1 Postswitch_i + \beta_2\ Interest\ rate\ spread_i + \beta_3\ Postswitch_i \times\ Interest\ rate\ spread_i\ +\ Listing\ characteristics\ controls + Macroeconomic\ environment\ controls + \varepsilon_i. \quad (6)$$

Table 9 reports the regression results. As in Table 8, we report the results of unweighted logit regression (column 1), inverse propensity score weighted regression (column 2) and unweighted logit regression using the subsample of repeat borrowers (column 3). The negative coefficients of the interaction term in all three columns suggest that funding decisions are less affected by loan pricing after the switch.

An important question to answer is why the funding probability increases under the less-efficient posted-price regime. Einav et al. (2018) provide one possible explanation for this phenomenon. The authors discover that in online markets with both auctions and posted-pricing regimes, a trade-off exists between price discovery and convenience. In online markets, the fact that consumers are increasingly in favor of posted prices is driven by a change in preferences toward convenience shopping. It is expected that a similar trade-off between the loan pricing discovery of auctions and convenience of post prices also exists in the online peer-to-peer lending market, and lenders have increased their preference for a less time-consuming posted-price regime.

5.2 Impact on the platform

Following the standard practice of the risk-based pricing literature, we thus far have been using the estimated default probability as the measure of loan credit risk. However, analyzing the realized profit of Prosper before and after the regime switch helps elucidate Prosper's profit from loans with different realized default statuses. Prospers' profits are mainly generated from two sources: origination fees charged to borrowers and servicing fees charged to lenders. The origination fee is a one-time fee charged to borrowers when loans are funded. It is calculated as a percentage ranging from 2.4% to 5% of the amount borrowed, depending on the Prosper credit rating. The origination fees are taken from funds before the loan proceeds are transferred to the borrower. Lenders pay an annual loan servicing fee to Prosper, set at 1% per annum of the outstanding principal balance of the corresponding borrower loan prior to applying the borrower's current payment. Prosper charges a servicing fee for every borrower payment received before transferring to lenders. Thus, the welfare of the platform depends not only on the funding probability but also on the repayments of funded loans. To estimate fee collection, we first estimate the origination fee for each loan according to the corresponding loan's Prosper rating. For ratings AA through HR, the estimated origination fee charging percentages are 2.40%, 2.83%, 3.27%, 3.70%, 4.13%, 4.57%, and 5.00%, respectively. We then obtain the cumulative servicing fees collected for each loan from the dataset obtained from Prosper. Then, the sum of fees collected for each loan is calculated as the sum of the cumulative servicing fee and estimated origination fee.

We first calculate the sum of profits from fully paid and defaulted loans before and after the regime switch and present them in Panel A of Table 10. The ratio of the sum of profits of fully paid loans under posted pricing to the sum under auctions (2.17) is lower than the ratio for defaulted loans (3.25), which confirms that the increase in total profits under posted prices primarily comes from high-risk loans. In Panel B, we summarize the sum of profits by loan credit ratings before and after the regime switch. The total fees collected from loans with AA ratings decrease by 11%. The percentage increase in profits for loans with the E rating is 380.16%, which is the highest among all credit grades.

We then empirically test the changes in profits before and after the regime switch by estimating an OLS regression with the calculated sum of fees charged for each loan set as dependent variables and the postswitch indicator set as the regressor of interest. The regression specifications are as follows:

$$Sum\ of\ fees_i = \beta_0 + \beta_1 Postswitch_i + \beta_2\ Loan\ amont_i + \beta_3\ Actual\ default_i$$
$$+\beta_4\ Postswitch_i * Actual\ default_i + \varepsilon_i \qquad (7)$$

Panel C of Table 10 reports the OLS regression results. In column 1, we control for the loan amount and actual default indicator. The positive coefficient of the postswitch indicator suggests that Prosper's profits are significantly increased under posted prices. Borrowers taking larger loans also contribute to a significant increase in profits. The coefficient of the actual default indicator, however, suggests that defaulted loans generate higher profits. According to Prosper's fee structure, the profits of the platform also depend on how the default risk changes after the switch to the posted price. In column 2, we add an interaction term for the postswitch indicator and actual default indicator. The interaction term is not significant, meaning that Prosper's increased fee comes from originating more risky loans rather than charging a higher fee for each dollar of risky loans under the posted price. The rest of the results in column (2) remain consistent with column (1). Overall, results are consistent with Hypothesis 2.

5.3 Impact on lenders

When loan pricing is less sensitive to credit risk, lenders are expected to be compensated less for credit risk. To test whether lenders earn lower investment returns after the regime switch, we estimate an OLS regression to test the differential effect of the loan spread on lenders' P&L of investing. The dependent variable, the P&L of investing, is the present value of payments received by lenders, using risk-free rate as the discount rate, normalized to the loan amount minus one for each loan. If the P&L of investing equals zero, the lender earns a risk-free return on the loan. If the P&L of investing is greater than zero, the loan is profitable. If the P&L of investing is less than zero, it indicates that the lender bears a loss from investing in the loan. The explanatory variables are the postswitch indicator, the loan spread, and the interaction term of the postswitch indicator and the loan spread. We also control for the loan characteristics and macroeconomic indicators. The regression specifications are as follows:

$$P\&L\ of\ Investing_i = \beta_0 + \beta_1 Postswitch_i + \beta_2 Loan\ spread_i$$
$$+\beta_3 Postswitch_i \times Loan\ spread_i + Loan\ characteristics\ controls +$$
$$Macroeconomic\ environment\ controls + \varepsilon_i. \qquad (8)$$

The key variable of interest is the coefficient of the interaction term. Table 11 reports the OLS regression results of model (8). We report four models: unweighted regression with and without control variables in models (1) and (2), respectively, and loan amount weighted regressions with and without controls in models (3) and (4), respectively. The negative coefficients of the interaction term in all four models suggest that lenders are less compensated for the credit risk taken under posted prices than under auctions.

Figure 6 shows whether lenders suffer a higher loss rate under the posted-price regime. We construct monthly portfolios with loans listed in each month within the main sample period. The loans listed in the same month are grouped into one monthly portfolio, amounting to 24 portfolios for the selected sample period. For each portfolio, we plot the percentage of loans with the P&L of investing less than zero for each month. The figure shows that the percentage of loans that generate less than risk-free returns vastly increased after the regime switch. These results thus support Hypothesis 3.

We view these results as consistent with the importance of incentives in the peer-to-peer lending market. The logic of the impact of less risk-based pricing is straightforward: Lower credit risk sensitivity indicates that the premium paid per unit of credit risk becomes significantly lower under posted prices and therefore is more attractive to high-risk borrowers. Less risk-based pricing generates higher profits for the platform, mainly from riskier loans, but lowers lenders' credit risk compensation. The incentive of the platform to increase profits by choosing less risk-based pricing without bearing the loss for bad lending points to the possibility of moral hazard issues.

5.4 Ex post tests

Our results thus far show that the posted-price regime is less efficient at pricing borrowers' estimated default risk than auctions. An important follow-up question is whether realized default risk is truly less efficiently priced under posted prices or whether the result is driven by our estimation of credit risk. As a further test of the main result, we substitute the predicted probability of default in model (3) with the actual default indicator. The actual default indicator is a dummy variable that equals one if a loan is defaulted based on its repayment performance and zero otherwise. The result of the estimation is reported in column 1 of Table 12. The key interaction term remains negative and significant. Therefore, the results with both the actual and estimated probability of default suggest that credit risk is less priced in the interest rate after the pricing regime switches to posted prices. We further introduce Prosper's credit rating to examine the correlation between loan spreads and credit risk. According to Prosper's internal credit rating[24], we classify loans into seven classes of risk and construct a credit grade variable, with 1 being the lowest risk level and 7 being the highest. We run the estimation of loan spreads in model (3), and the results of the regression are reported in column (2) of Table 12. The key interaction term of the credit rating and postswitch indicator remains negative and significant, suggesting that loan spread sensitivity to credit risk decreases after Prosper switches to the posted price and that this reduction is greater for high-risk grade borrowers.

5.5 Tests with data under upgraded posted prices

In the summer of 2012, Prosper introduced more granular risk-based pricing based on Estimated Loss Rate (ELR) as opposed to Prosper ratings. This change has led to improvement in risk scoring (Vallee and Zeng 2019, Balyuk and Davydenko 2019). We conduct a robustness test using data after the change. The post-upgrade dummy equals one when the loan is requested on Prosper from January 1, 2013, to December 31, 2013 and it is zero when the loan is requested from December 1, 2009, to November 30, 2010.

Table 13 presents the regression results of loan spread against the post-upgrade dummy, three proxies of default risk, and their interaction with the post-upgrade dummy. The three proxies of default are (1) the predicted probability of default measured by the logit regression (Column 1); (2) the actual default dummy, which is a dummy variable that equals to one if a loan is defaulted based on its repayment performance and zero otherwise (Column 2); and (3) Prosper grade, which is a credit grade variable based on Prosper internal credit rating with 1 being the lowest risk level and 7 being the highest risk level (Column 3). The dependent variable, loan spread, is the borrower's contract interest rate minus the one-year daily treasury rate on the loan origination date. Other control variables include the loan amount and macroeconomic controls.

[24]Prosper indicates that it sets loan interest rates based on borrowers' Prosper rating as well as on factors such as loan terms, the general economic environment, and group affiliation.

Results from all three columns show that the sensitivity to default risk significantly reduced even after Prosper introduced more granular risk-based pricing.

6. Conclusion

In this paper, we explore risk-based pricing in peer-to-peer lending. Specifically, we examine a regime switch from the auction to the posted-price mechanism occurring on a large online peer-to-peer lending platform, Prosper.com, by investigating whether credit risk, measured by the estimated probability of default and the hazard rate, is priced differently under the two regimes. We find that under posted prices, loan pricing is less sensitive to credit risk; the platform collects higher profits; lenders are less compensated for the credit risk taken, and borrowers experience less credit rationing. In robustness exercises, we rule out the possibility that the main result is affected by the measure of credit risk, the endogeneity of the estimation of loan spreads, and sample selection bias.

Our paper contributes to the broader literature on risk-based pricing by offering the first study exploring risk-based pricing in online peer-to-peer lending markets. As a significant supplier of credit to consumers, the global peer-to-peer lending market has grown rapidly; however, little is known about pricing practices in this sector. Our study fills this gap. Furthermore, our paper contributes to the growing literature concerning online peer-to-peer lending as well as the literature concerning market mechanisms by documenting how two commonly used pricing mechanisms set loan spreads according to borrowers' credit risks. Although the posted-price regime is favored by many platforms in the US, its pricing effectiveness is not guaranteed.

While our main analysis is based on Prosper's pricing regime choice, the findings of loan pricing generalize to other peer-to-peer lending platforms. We believe that the incentives of all stakeholders (borrowers, lenders, and platforms) are similar on most, if not all, peer-to-peer lending platforms. Additionally, even though the two largest US peer-to-peer lending platforms and most of the other platforms in the US use posted-price mechanisms, many foreign peer-to-peer lending platforms still use auctions. Therefore, our study carries important relevance in the current global peer-to-peer lending market.

Our results point to the possibility of moral hazard issues created by competing over the market share in the peer-to-peer lending industry, corresponding to the widespread belief that competition over market share leads to increased risk-taking and reduced lending standards in a "race to the bottom." The implications of these findings are important for policymakers as well as market designers by calling for regulation of competition among peer-to-peer lending platforms.

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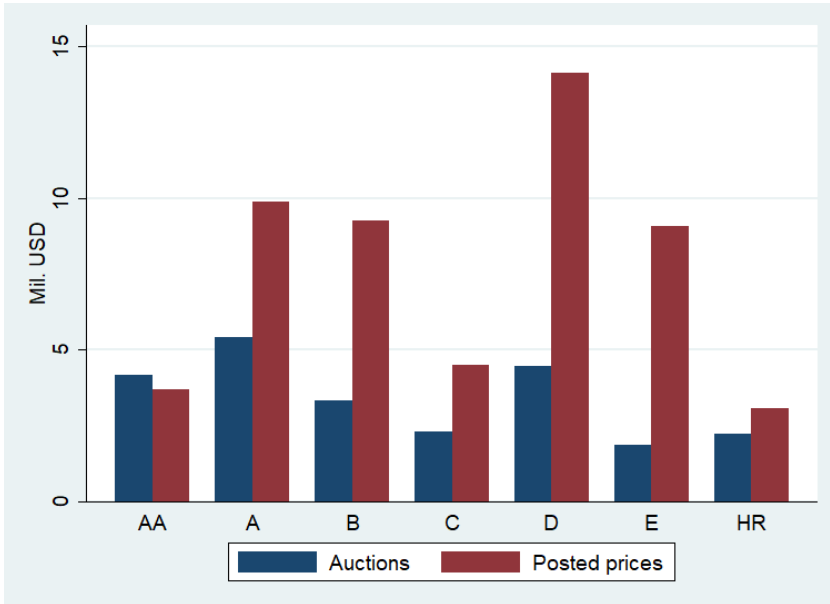
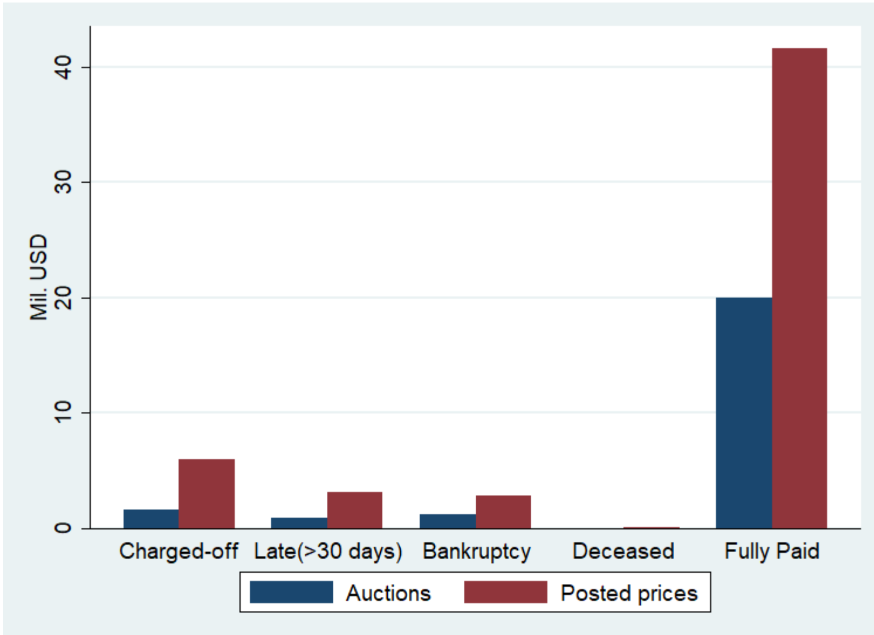


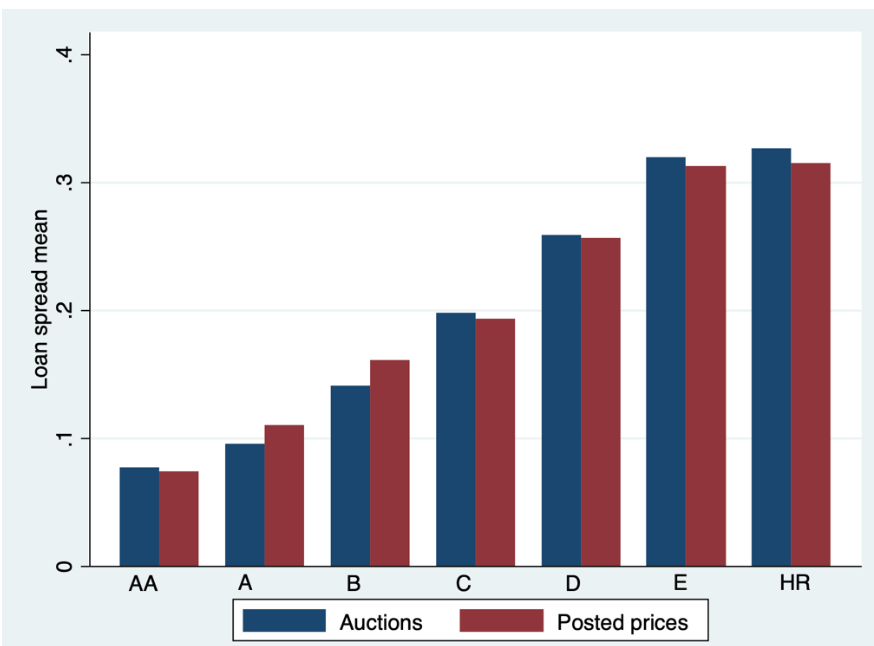
Panel A: Total loan amount funded

Panel B: Percentage of loan amount funded

Figure 1. Funded Loans Under Auctions and Posted Prices Across Different Borrower Credit Grades. Panel A plots the loan amount funded by Prosper.com, in millions of USD, under auctions (blue bar) and posted prices (red bar) across different borrower credit grades during our sample period of December 1, 2009, to December 31, 2011, except for December 2010. In contrast, Panel B presents the percentages of the amount funded under auctions and posted prices across different borrower credit grades within the same period.

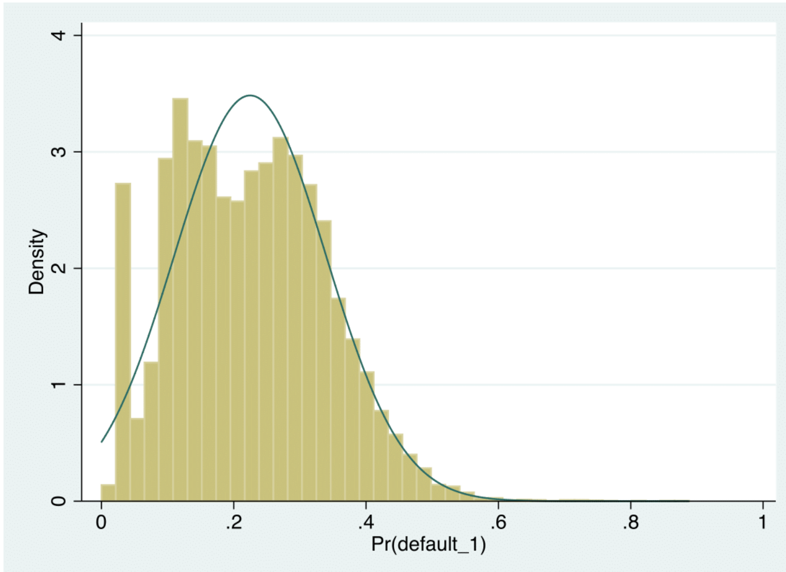


Panel A: Loan Status Distribution

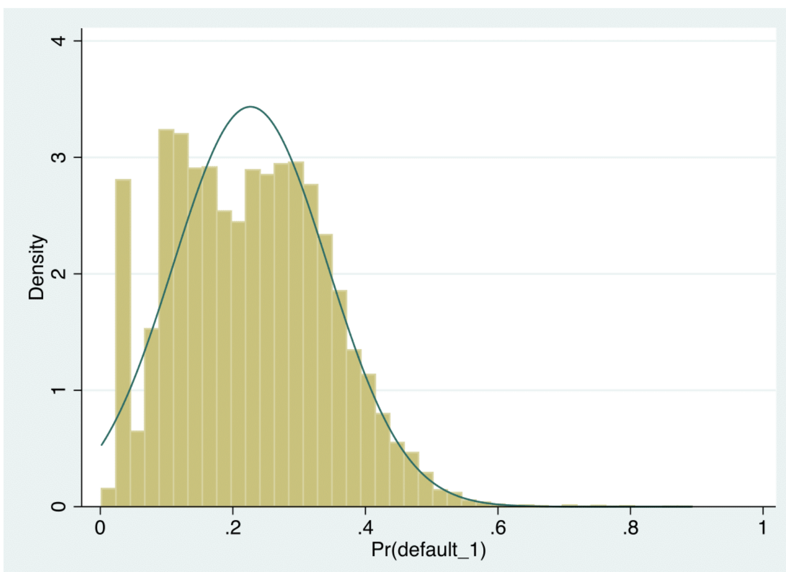


Panel B: Loan spread distribution

Figure 2. Loan Status and Loan Spread Distribution Under Auctions and Posted Prices. Panel A illustrates the distributions of loan status under auctions (from December 1, 2009 to November 30, 2010) and posted prices (from January 1, 2011 to December 31, 2011). The figure presents the original value of loans funded in millions of USD by credit status at loan maturity. Panel B presents the mean of loan spread under auctions and posted prices across different borrower credit grades within the same period.

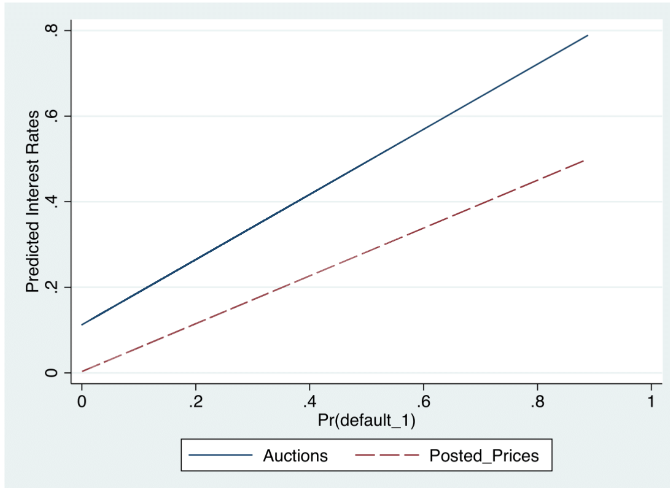


Panel A: Unweighted logit estimation

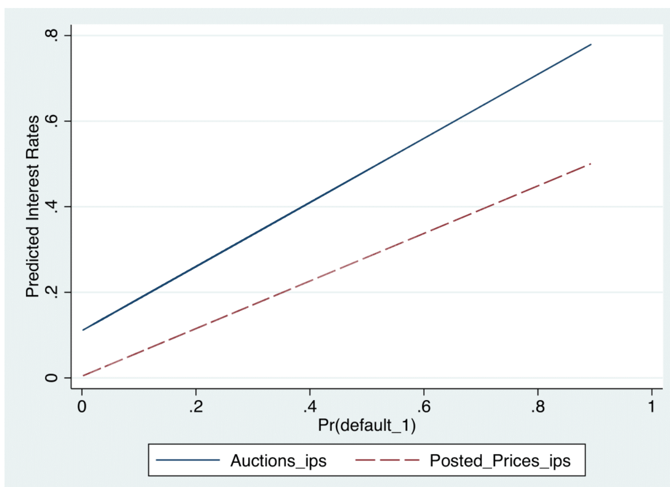


Panel B: Inverse propensity score weighted logit estimation

Figure 3. Probability of Default Distribution. Panel A plots the density function of default probability from unweighted logit estimation using the peer-to-peer loan default data in our sample period of December 1, 2009 to December 31, 2011 except for December 2010. Panel B plots the density function of default probability from inverse propensity score weighted logit estimation using the same loan default data.



Panel A: Probability of default estimated by unweighted logit regression



Panel B: Probability of default estimated by inverse propensity score weighted logit regression

Figure 4. Differential Effect of the Probability of Default between Auctions and Posted Prices. We present the functions of loan spreads against predicted default risk, estimated from Equation (3). The solid line shows the functions for loans funded under auctions, whereas the dashed line shows the functions for loans funded under posted prices. The predicted default risk in Panel A is estimated from unweighted logit regression, whereas the predicted default risk in Panel B is obtained from inverse propensity score weighted logit regression. The loan spread is predicted by the probability of default for each loan, and other significant variables are set to their mean values for the whole sample period.

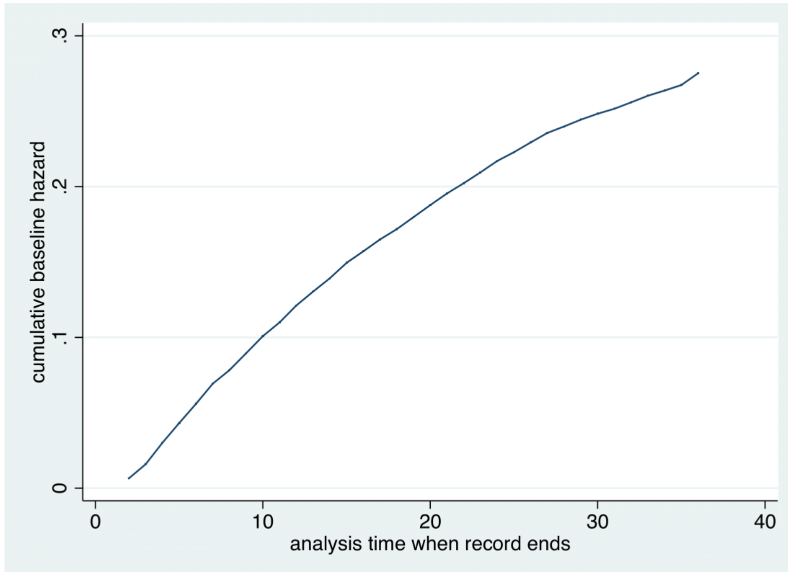


Figure 5. Cumulative Baseline Hazard. The plot shows the cumulative baseline hazard function of the Cox proportional hazard model of Equation (4) using our sample period of December 1, 2009 to December 31, 2011 except for December 2010.

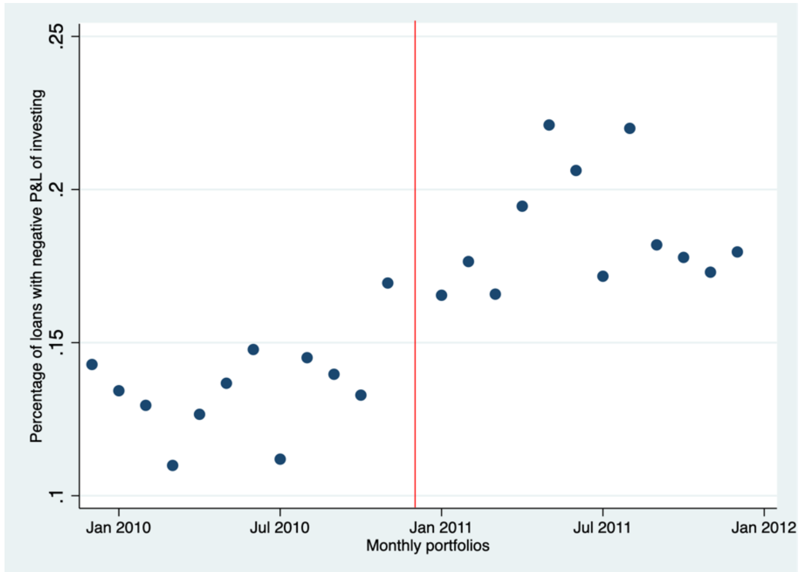


Figure 6. Scatter Plot of the Percentage of Loans that Generate Negative P&L. This figure shows the percentage of loans that generate negative P&L by listed month. The sample period runs from December 1, 2009 to December 31, 2011 except for December 2010. Hence, 24 monthly portfolios are constructed. For each monthly portfolio, we plot the percentage of loans with negative P&L of investing. The vertical line denotes the month of the pricing regime switch.

Table 1. Summary Statistics

Notes: This table presents general summary statistics of the corresponding variables for a sample of 37,335 listings and 13,380 loans for the sample period of December 2009 to December 2011 (excluding December 2010). The table reports the means and standard deviations of the variables for all listings and loans as well as the subgroup of listings and loans originating under auctions and under posted prices. Univariate t tests are also conducted for each variable between auctions and posted prices. The summary statistics of listings and loans are presented in Panels A and B, respectively. A detailed description of the variables is provided in Appendix B.

Panel A. Summary statistics of listings

	All Listings		Auctions		Posted Prices		T test	
	Mean	SD	Mean	SD	Mean	SD	t-stat.	p value
Listing amount	6,973.32	5,041.15	6,985.99	5,326.35	6,954.06	4,574.28	0.60	0.55
DTI with Prosper loan	0.26	0.25	0.28	0.25	0.24	0.24	15.86	0.00
Homeowner	0.53	0.50	0.54	0.50	0.50	0.50	6.68	0.00
Group member	0.06	0.23	0.07	0.25	0.04	0.19	12.12	0.00
Years employed	7.49	7.26	7.20	6.97	7.94	7.67	-9.66	0.00
Stated monthly income	5,548.09	10,061.34	5,300.82	8,463.28	5,923.59	12,081.34	-5.85	0.00
Amount delinquent	1,137.97	6,881.85	932.58	5,362.55	1,449.85	8,686.30	-7.11	0.00
Bankcard utilization	0.53	0.34	0.55	0.35	0.51	0.34	11.33	0.00
Current credit lines	9.52	5.51	9.81	5.58	9.09	5.39	12.40	0.00
Current delinquencies	0.46	1.30	0.44	1.23	0.51	1.40	-5.33	0.00
Credit history length	16.27	7.87	15.78	7.70	17.00	8.07	-14.69	0.00
Revolving balance	21,228.65	39,722.31	22,766.51	40,661.92	18,893.35	38,134.31	9.23	0.00
Delinquencies last 7 years	3.62	8.99	3.28	8.52	4.14	9.62	-9.02	0.00
Public records last 10 years	0.26	0.63	0.24	0.61	0.29	0.66	-7.13	0.00
Public records last 12 months	0.01	0.14	0.01	0.13	0.02	0.14	-1.85	0.06
Inquiries last 6 months	1.47	2.04	1.53	2.11	1.37	1.91	7.45	0.00
ScoreX score	703.34	46.72	702.18	47.40	705.11	45.62	-5.94	0.00
Prosper score	5.93	2.41	5.88	2.50	6.02	2.27	-5.77	0.00
N	37,335		22,511		14,824			

Panel B. Summary statistics of funded loans

	All Loans		Auctions		Posted Prices		T test	
	Mean	SD	Mean	SD	Mean	SD	t-stat.	p value
Amount borrowed	5,789.17	3,990.72	4,861.27	3,759.86	6,325.6	4,021.99	-20.78	0.00
Borrower rate	0.22	0.09	0.21	0.10	0.23	0.08	-14.99	0.00
DTI with Prosper loan	0.23	0.19	0.22	0.16	0.24	0.20	-5.26	0.00
Homeowner	0.54	0.50	0.54	0.50	0.53	0.50	1.52	0.13
Group member	0.07	0.25	0.10	0.29	0.05	0.21	10.57	0.00
Years employed	7.69	7.27	7.27	6.93	7.94	7.45	-5.13	0.00
Stated monthly income	5,599.56	7,811.32	5,408.18	3,712.64	5,710.21	9,396.72	-2.16	0.03
Amount delinquent	1,092.04	7,557.85	511.07	4,106.43	1,427.95	8,949.59	-6.77	0.00
Bankcard utilization	0.54	0.33	0.52	0.34	0.55	0.33	-4.52	0.00
Current credit lines	9.59	5.36	9.73	5.19	9.50	5.45	2.38	0.02
Current delinquencies	0.43	1.30	0.29	1.08	0.50	1.41	-9.26	0.00
Credit history length	16.58	7.63	15.74	7.47	17.07	7.68	-9.81	0.00
Revolving balance	19,721.51	36,910.49	19,544.74	33,543.58	19,823.72	38,725.47	-0.42	0.67
Delinquencies last 7 years	3.74	9.19	2.87	7.90	4.25	9.82	-8.37	0.00
Public records last 10 years	0.27	0.64	0.23	0.58	0.30	0.67	-6.45	0.00
Public records last 12 months	0.01	0.13	0.01	0.11	0.02	0.14	-1.79	0.07
Inquiries last 6 months	1.14	1.64	1.00	1.51	1.22	1.70	-7.45	0.00
ScoreX score	705.25	47.36	709.47	49.90	702.81	45.64	7.85	0.00
Prosper score	6.55	2.25	7.41	1.99	6.05	2.24	35.16	0.00
N	13,380		4,902		8,478			

Table 2. Loan Distribution by Credit Rating

Notes: This table presents the loan distribution according to Prosper's internal credit rating. Prosper uses borrowers' credit information to classify loans from rating AA to rating HR according to credit risk, with rating AA representing the lowest risk and HR representing the highest risk.

Credit grade	Number of loans	Percent	Amount of loan provided ($)	Percent
Panel A. All funded loans				
AA	969	7.24%	7,895,743	10.19%
A	2,034	15.20%	15,283,182	19.73%
B	1,676	12.53%	12,609,213	16.28%
C	1,223	9.14%	6,798,193	8.78%
D	3,571	26.69%	18,596,282	24.01%
E	2,300	17.19%	10,942,697	14.13%
HR	1,607	12.01%	5,333,756	6.89%
Total	13,380	100.00%	77,459,066	100.00%
Panel B. Loans funded under auctions				
AA	610	12.44%	4,183,964	17.56%
A	924	18.85%	5,411,516	22.71%
B	444	9.06%	3,352,367	14.07%
C	583	11.89%	2,307,458	9.68%
D	1,103	22.50%	4,467,562	18.75%
E	530	10.81%	1,863,428	7.82%
HR	708	14.44%	2,243,639	9.42%
Total	4,902	100.00%	23,829,934	100.00%
Panel C. Loans funded under posted prices				
AA	359	4.23%	3,711,779	6.92%
A	1,110	13.09%	9,871,666	18.41%
B	1,232	14.53%	9,256,846	17.26%
C	640	7.55%	4,490,735	8.37%
D	2,468	29.11%	14,128,720	26.35%
E	1,770	20.88%	9,079,269	16.93%
HR	899	10.60%	3,090,117	5.76%
Total	8,478	100.00%	53,629,132	100.00%

Table 3. Loan Distribution by Payment Status

Notes: This table presents the loan distribution according to loan status. All loans in the sample are mature loans. A charged-off status denotes that the loan has uncollectible payments. A late status denotes that the borrower has at least one payment that is more than 30 days late. A bankruptcy status denotes that the borrower filed for bankruptcy. A deceased status denotes that the borrower passed away. A fully paid status denotes that the borrower fully paid the principle and interest.

Payment status	Number of loans	Percent	Amount ($)	Percent	Unpaid principal ($)
Panel A. All funded loans					
Charged-off	1.462	10.93%	7,693,997	9.93%	5,179,657
Late (>30 days)	745	5.57%	4,084,367	5.27%	-
Bankruptcy	799	5.97%	4,098,580	5.29%	2,839,897
Deceased	1	0.01%	9,330	0.01%	40
Fully paid	10,373	77.53%	61,569,622	79.49%	-
Total	13,380	100.00%	77,459,066	100.00%	8,019,594
Panel B. Loans funded under auctions					
Charged-off	398	8.12%	1,682,956	7.06%	1,136,031
Late (>30 days)	205	4.18%	889,337	3.73%	-
Bankruptcy	285	5.81%	1,242,700	5.21%	821,210
Fully paid	4,014	81.88%	20,014,941	83.99%	-
Total	4,902	100.00%	23,829,934	100.00%	1,957,241
Panel C. Loans funded under posted prices					
Charged-off	1,064	12.55%	6,011,041	11.21%	4,043,626
Late (>30 days)	540	6.37%	3,195,030	5.96%	
Bankruptcy	514	6.06%	2,855,880	5.33%	2,018,687
Deceased	1	0.01%	9,330	0.02%	40
Fully paid	6,359	75.01%	41,554,681	77.49%	
Total	8,478	100.00%	53,629,132	100.00%	6,062,353

Table 4. Probability of Default Estimation

Notes: This table presents the unweighted logit estimation (column 1) and inverse propensity score (IPS) weighted estimation (column 2) logit estimation of the probability of default. The dependent variable is a dummy variable that equals one if a loan is defaulted and zero otherwise. A detailed description of the variables used in the regression is shown in Appendix B. Robust standard errors appear in parentheses below the coefficients; * p<0.1; ** p<0.05; *** p<0.01.

	(1) Unweighted	(2) IPS Weighted
DTI with Prosper loan	0.544***	0.565***
	(0.190)	(0.195)
Homeowner	0.0318	0.0141
	(0.0534)	(0.0544)
Group member	-0.377***	-0.320***
	(0.0928)	(0.101)
Years employed	-0.00131	-0.00144
	(0.00318)	(0.00324)
Stated monthly income (thousand)	-0.0167	-0.0115
	(0.0277)	(0.0252)
Amount delinquent (thousand)	-0.00272	-0.00256
	(0.00317)	(0.00315)
Bankcard utilization	-0.400***	-0.402***
	(0.0813)	(0.0824)
Current credit lines	-0.0358***	-0.0365***
	(0.00617)	(0.00626)
Current delinquencies	0.0556***	0.0503***
	(0.0175)	(0.0180)
Credit history length	0.0111***	0.0107***
	(0.00321)	(0.00327)
Revolving balance (million)	0.502	0.0162
	(1.048)	(1.026)
Delinquencies last 7 years	-0.00543**	-0.00506*
	(0.00272)	(0.00276)
Public records last 10 years	0.0519	0.0515
	(0.0344)	(0.0349)
Public records last 12 months	0.00805	0.0325
	(0.153)	(0.155)
Inquiries last 6 months	0.0681***	0.0690***
	(0.0150)	(0.0155)
ScoreX score	-0.00251***	-0.00223***
	(0.000679)	(0.000692)
Prosper score	-0.0342*	-0.0264
	(0.0179)	(0.0187)
Cons	-0.779	-1.048*
	(0.594)	(0.606)
Prosper grade fixed effect	Yes	Yes
N	13,380	13,380

Table 5. Loan Spread and Probability of Default

Notes: This table presents the OLS regression results of loan spread on the postswitch dummy, the predicted probability of default and its interaction with the postswitch dummy. The predicted probability of default is measured by unweighted and IPS weighted logit regressions. The dependent variable, loan spread, is the borrower's contract interest rate minus the one-year daily treasury rate of the loan origination date. The postswitch dummy equals one when the loan is funded under posted pricing and zero when the loan is funded using auctions. Column (1) shows the unweighted regression result without borrower characteristics controls, and column (2) shows the unweighted regression result with controls. Column (3) shows the inverse propensity score weighted regression result without control variables, and column (4) shows the inverse propensity score weighted regression result with controls. Borrower characteristics controls are independent variables included in model (1). Other control variables include the loan amount and macroeconomic controls. Macroeconomic control variables include Housing Price Index and unemployment rate. Alternatively, we also control for fixed effects, which includes month FE and ScoreX bin FE. Although the sample size becomes smaller, the significance of results remains the same. Robust standard errors appear in parentheses below the coefficients; * p<0.1; ** p<0.05; *** p<0.01.

	(1)	(2)	(3)	(4)
	Unweighted	Unweighted	IPS Weighted	IPS Weighted
Postswitch	0.0359***	0.00862***	0.0401***	0.00835***
	(0.00281)	(0.000984)	(0.00273)	(0.000916)
Pr. default	0.745***	0.0412***	0.727***	0.0377***
	(0.00772)	(0.0110)	(0.00727)	(0.00983)
Postswitch*Pr. default	-0.172***	-0.0568***	-0.160***	-0.0567***
	(0.00984)	(0.00384)	(0.00942)	(0.00368)
Amount borrowed (million)	-0.851***	0.825***	-1.046***	0.675***
	(0.100)	(0.0477)	(0.0974)	(0.0442)
Cons	-0.00997	0.0373***	-0.0269	0.0311***
	(0.0280)	(0.0116)	(0.0273)	(0.00989)
Borrower characteristics	No	Yes	No	Yes
Macroeconomic controls	Yes	Yes	Yes	Yes
N	13,380	13,380	13,380	13,380
R^2	0.719	0.948	0.735	0.957

Table 6. Loan Spread and Hazard Rate

Notes: This table presents the OLS regression results of loan spread on the postswitch dummy, the hazard rate and its interaction with the postswitch dummy. The dependent variable is loan spread, which is the borrower's contract interest rate minus the one-year daily treasury rate of the loan origination date. The hazard rate represents the expected number of loan defaults that can happen at a time given that the default has not yet occurred. The hazard rate was estimated at 24 and 36 months using the Cox proportional hazard model. The postswitch dummy equals one when the loan is funded under posted pricing and zero when the loan is funded using auctions. The control variables are the loan amount and macroeconomic controls. Macroeconomic control variables include Housing Price Index and unemployment rate. Robust standard errors appear in parentheses below the coefficients; * p<0.1; ** p<0.05; *** p<0.01.

	24 months	36 months
Postswitch	0.00515*	0.0110***
	(0.00294)	(0.00275)
Hazard rate	0.359***	0.366***
	(0.00261)	(0.00259)
Postswitch* Hazard rate	-0.00844**	-0.0198***
	(0.00344)	(0.00337)
Amount borrowed(million)	0.147	0.196*
	(0.102)	(0.100)
Cons	-0.183***	-0.157***
	(0.0263)	(0.0258)
Macroeconomic controls	Yes	Yes
N	13,380	13,380
R^2	0.768	0.776

Table 7. Loan Spread and Probability of Default: Subsample of Repeat Borrowers

Notes: This table presents the OLS regression results of loan spread on the postswitch dummy, the predicted probability of default and its interaction with the postswitch dummy using a subsample of borrowers who requested loans both before and after the regime switch during the sample period. The dependent variable is loan spread, which is the borrower's contract interest rate minus the one-year daily treasury rate of the loan origination date. The predicted probability of default is estimated by unweighted logit regressions. The postswitch dummy equals one when the loan is funded under posted pricing and zero when the loan is funded using auctions. Control variables are the loan amount and macroeconomic controls. Macroeconomic control variables include Housing Price Index and unemployment rate. Alternatively, we also control for fixed effects, which includes month FE and ScoreX bin FE. Although the sample size becomes smaller, the significance of results remains the same. Robust standard errors appear in parentheses below the coefficients; * $p<0.1$; ** $p<0.05$; *** $p<0.01$.

	Dependent Var: Loan Spread
Postswitch	0.0408***
	(0.00772)
Pr. default	1.016***
	(0.0379)
Postswitch*Pr. default	-0.509***
	(0.0405)
Amount borrowed (million)	-2.799***
	(0.289)
Cons	-0.00856
	(0.0834)
Macroeconomic controls	Yes
N	3,012
R^2	0.499

Table 8. Funding Probability Before and After the Regime Switch by Credit Rating

Notes: This table presents the logit regression results of the funding indicator on the postswitch dummy and control variables for listing characteristics and the macroeconomic environment. These regressions examine the impact of pricing regime switching on the probability of receiving a loan for both the full sample and borrower credit grade subsamples. The dependent variable, the funding indicator, equals one if the listing receives funding and equals zero if it does not. The postswitch dummy equals one when the listing is requested under posted pricing and zero when the listing is requested under auctions. Listing characteristics controls include variables in borrowers' credit profiles. Macroeconomic control variables include Housing Price Index and unemployment rate. Panel A presents the unweighted logit estimates of the regime change effect on funding probability. Panel B presents the inverse propensity score weighted logit regression result. Panel C presents the logit regression results obtained from a subsample of borrowers who requested loans before and after the regime switch during the sample period. Robust standard errors appear in parentheses below the coefficients; * p<0.1; ** p<0.05; *** p<0.01.

	All Listings	AA	A	B	C	D	E	HR
Panel A: unweighted								
Postswitch	1.076***	0.237	0.462***	0.258	2.249***	1.297***	1.405***	1.137***
	(0.0604)	(0.253)	(0.174)	(0.166)	(0.322)	(0.115)	(0.154)	(0.142)
Listing amount	-0.138***	-0.0428***	-0.0840***	-0.0745***	-0.143***	-0.205***	-0.266***	-0.417***
(thousand)	(0.00340)	(0.00775)	(0.00680)	(0.00881)	(0.0137)	(0.00802)	(0.0161)	(0.0210)
Cons	14.04***	-3.132	21.88***	16.92***	-0.269	10.27***	12.31***	17.10***
	(1.087)	(6.171)	(3.232)	(2.801)	(5.625)	(1.935)	(2.794)	(2.751)
Prosper grade fixed effect	Yes							
Macroeconomic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Listing characteristics controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	37,335	2,172	4,017	3,267	2,936	9,445	4,833	10,658
Panel B: IPS weighted								
Postswitch	1.049***	0.219	0.467***	0.258	2.264***	1.294***	1.329***	1.105***
	(0.0612)	(0.255)	(0.176)	(0.168)	(0.330)	(0.116)	(0.157)	(0.148)
Listing amount	-0.132***	-0.0458***	-0.0853***	-0.0755***	-0.136***	-0.198***	-0.251***	-0.430***
(thousand)	(0.00349)	(0.00800)	(0.00691)	(0.00902)	(0.0137)	(0.00839)	(0.0164)	(0.0221)
Cons	13.66***	-3.706	22.30***	15.98***	-1.816	9.553***	11.45***	16.11***
	(1.101)	(6.410)	(3.296)	(2.831)	(5.821)	(1.944)	(2.813)	(2.873)
Prosper grade fixed effect	Yes							
Macroeconomic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Listing characteristics controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	37,335	2,172	4,017	3,267	2,936	9,445	4,833	10,658
Panel C: subsample of repeat borrowers								
Postswitch	1.378***	0.259	0.276	-0.0180	1.592**	1.154***	2.177***	2.435***
	(0.177)	(0.932)	(0.510)	(0.704)	(0.633)	(0.332)	(0.462)	(0.446)
Listing amount	-0.170***	-0.110***	-0.130***	-0.0788**	-0.135***	-0.191***	-0.336***	-0.523***

(thousand)	(0.00992)	(0.0335)	(0.0221)	(0.0338)	(0.0274)	(0.0206)	(0.0505)	(0.0531)
Cons	12.43***	2.627	24.64**	17.57	7.098	12.35**	5.100	8.552
	(3.263)	(20.88)	(10.13)	(12.02)	(11.30)	(5.704)	(9.366)	(8.402)
Prosper grade fixed effect	Yes							
Macroeconomic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Listing characteristics controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	5,666	271	790	354	683	1,396	845	1,325

Table 9. The Impact of Interest Rate Spread on Funding Probability Before and After the Regime Switch

Notes: This table presents the logit regression results of the funding indicator on the postswitch dummy, the interest rate spread, and its interaction with the postswitch dummy. The dependent variable, the funding indicator, equals one if the listing receives funding and equals zero if the listing does not receive funding. The postswitch dummy equals one when the listing is requested under posted pricing and zero when the listing is requested under auctions. The interest rate spread equals the contract interest rate minus the one-year daily treasury rate of the loan origination date if the listing is funded and equals borrowers' requested interest rate minus the one-year daily treasury rate of the listing start date if the listing is not funded. Listing characteristics controls include variables in borrowers' credit profiles. The interaction terms of the Prosper credit grade dummies and postswitch dummy are also included since the credit grade is highly correlated with the interest rate spread. Macroeconomic control variables include Housing Price Index and unemployment rate. Column 1 presents the unweighted logit regression result. Column 2 presents the inverse propensity score (IPS) weighted logit regression result. Column 3 presents the logit regression results obtained from a subsample of borrowers who requested loans both before and after the regime switch during the sample period. Robust standard errors appear in parentheses below the coefficients; * p<0.1; ** p<0.05; *** p<0.01.

	(1) Unweighted	(2) IPS Weighted	(3) Subsample of repeat borrowers
Postswitch	2.206***	2.275***	1.876***
	(0.172)	(0.171)	(0.488)
Interest rate spread	9.271***	9.707***	9.155***
	(0.384)	(0.400)	(0.846)
Postswitch*	-24.62***	-24.81***	-18.18***
Interest rate spread	(1.585)	(1.572)	(4.549)
Listing amount	-0.129***	-0.123***	-0.165***
(thousand)	(0.00361)	(0.00369)	(0.0102)
Cons	13.10***	12.39***	16.86***
	(1.099)	(1.112)	(3.372)
Prosper rating fixed effect	Yes	Yes	Yes
Macroeconomic controls	Yes	Yes	Yes
Listing characteristics controls	Yes	Yes	Yes
N	37,335	37,335	5,666

Table 10. Sum of Fees Before and After the Mechanism Switch

Notes: Panel A shows the distribution of total fees that Prosper collected by loan status before and after the regime switch, and Panel B shows the distribution of total fees collected by credit rating before and after the regime switch. Panel C of the table presents the OLS regression results of the sum of fees collected per loan on the postswitch dummy. The sum of fees collected per loan is calculated as the sum of the origination fee charged to the borrower and the cumulative servicing fee from lenders. The postswitch dummy equals one when the loan is funded under posted pricing and zero when the loan is funded using auctions. The control variables are the loan amount borrowed and actual default indicator. Robust standard errors appear in parentheses below the coefficients; * p<0.1; ** p<0.05; *** p<0.01.

Panel A. Total fees collected by loan status			
	Fully paid	Defaulted	
Posted prices	2,021,739	615,820	
Auctions	932,843	189,545	
Ratio	2.17	3.25	
Panel B. Total fees collected by credit rating			
	Auctions	Posted prices	Percentage increase
AA	149,854	132,921	-11.30%
A	223,371	403,178	80.50%
B	151,673	419,502	176.58%
C	111,878	222,653	99.01%
D	239,061	752,851	214.92%
E	107,481	516,075	380.16%
HR	139,070	190,379	36.89%

Panel C. Sum of fees regressed on the postswitch dummy		
	(1)	(2)
Postswitch	21.49***	21.97***
	(1.044)	(1.181)
Amount borrowed	0.0411***	0.0410***
	(0.000234)	(0.000234)
Actual default	7.767***	9.384***
	(1.070)	(1.820)
Postswitch*Actual default		-2.357
		(2.252)
Cons	28.00***	27.71***
	(1.129)	(1.182)
N	13,380	13,380
R^2	0.897	0.897

Table 11. P&L of Investing and Loan Spread

Notes: This table presents the OLS regression results of the P&L of investing on the postswitch dummy, the loan spread and its interaction with the postswitch dummy. The dependent variable is the P&L of investing. It is measured for each loan as the normalized present value of payments received by lenders to the loan size minus one. The loan spread is the borrower's interest rate minus the one-year daily treasury rate of the loan origination date. The posted prices dummy equals one when the loan is funded under posted pricing and zero when the loan is funded using auctions. Other specifications include loan characteristic controls and macroeconomic controls. Macroeconomic control variables include Housing Price Index and unemployment rate. Model (1) shows the unweighted regression result without control variables, and model (2) shows the unweighted regression result with controls. Model (3) shows the loan-size weighted regression result without control variables, and model (4) shows the loan-size weighted regression result with controls. Robust standard errors appear in parentheses below the coefficients; * $p<0.1$; ** $p<0.05$; *** $p<0.01$.

	(1) Unweighted	(2) Unweighted	(3) Loan-size weighted	(4) Loan-size weighted
Postswitch	0.0561***	0.0458**	0.0591***	0.0582***
	(0.0118)	(0.0179)	(0.0127)	(0.0187)
Loan spread	0.563***	0.553***	0.554***	0.547***
	(0.0497)	(0.0503)	(0.0573)	(0.0595)
Postswitch*	-0.399***	-0.403***	-0.417***	-0.422***
Loan spread	(0.0675)	(0.0680)	(0.0733)	(0.0736)
Amount borrowed		-0.668		-0.372
(million)		(0.666)		(0.731)
Cons	0.00508	0.134	0.00594	0.0502
	(0.00798)	(0.229)	(0.00934)	(0.229)
Macroeconomic controls	No	Yes	No	Yes
N	13,380	13,380	13,380	13,380
R^2	0.011	0.011	0.009	0.009

Table 12. Loan Spread, Actual Default and Prosper Rating

Notes: This table reports the results of ex post tests. The dependent variable is loan spread, which is the borrower's contract interest rate minus the one-year daily treasury rate of the loan origination date. The actual default indicator is a dummy variable that equals to one if a loan is defaulted based on its repayment performance and zero otherwise. Prosper grade is a credit grade variable. In particular, according to Prosper's internal credit rating, we classify loans into seven classes of risk and construct a credit grade variable, with 1 being the lowest risk and 7 being the highest. Column (1) presents the OLS regression results of loan spreads on the postswitch dummy, the actual default dummy and its interaction with the postswitch dummy. Column (2) presents the OLS regression results of loan spreads on the postswitch dummy, the borrower credit grade (Prosper grade) and its interaction with the postswitch dummy. Macroeconomic control variables include Housing Price Index and unemployment rate. Alternatively, we also control for fixed effects, which includes month FE and ScoreX bin FE. Although the sample size becomes smaller, the significance of results remains the same. Robust standard errors appear in parentheses below the coefficients; * $p<0.1$; ** $p<0.05$; *** $p<0.01$.

Dependent variable: Loan spread	Two alternatives of probability of default	
	(1)	(2)
	Actual default dummy	Prosper grade
Postswitch	0.0289***	0.00770***
	(0.00316)	(0.00140)
Actual default	0.0556***	
	(0.00321)	
Postswitch * Actual default	-0.0167***	
	(0.00356)	
Prosper grade		0.0476***
		(0.000175)
Postswitch *Prosper grade		-0.00136***
		(0.000230)
Amount borrowed (million)	-7.231***	0.909***
	(0.145)	(0.0572)
Cons	0.251***	-0.0398***
	(0.0458)	(0.0147)
Macroeconomic controls	Yes	Yes
N	13,380	13,380
R^2	0.182	0.927

Table 13. Loan Spread and Probability of Default: Auctions vs. Upgraded Posted Prices

Notes: This table reports the OLS regression results that compares the loan spread sensitivity to default under auctions (December 1, 2009, to November 30, 2010) and under upgraded posted prices (January 1, 2013, to December 31, 2013). This table presents the results of loan spread on the post-upgrade dummy, three proxies of default and their interaction with the post-upgrade dummy. The three proxies of default are (1) predicted probability of default, which is measured by the logit regression; (2) the actual default dummy, which is a dummy variable that equals to one if a loan is defaulted based on its repayment performance and zero otherwise; and (3) prosper grade, which is a credit grade variable. The dependent variable, loan spread, is the borrower's contract interest rate minus the one-year daily treasury rate of the loan origination date. The posts-upgrade dummy equals one when the loan is requested on Prosper from January 1, 2013, to December 31, 2013; and zero when the loan is requested from December 1, 2009, to November 30, 2010. Column (1) shows the OLS regression result of loan spreads on the post-upgrade dummy, the predicted probability of default and its interaction with the post-upgrade dummy. Column (2) presents the OLS regression results of loan spreads on the post-upgrade dummy, the actual default dummy, and its interaction with the post-upgrade dummy. Column (3) presents the OLS regression results of loan spreads on the post-upgrade dummy, the borrower credit grade, and its interaction with the post-upgrade dummy. Other control variables include the loan amount, macroeconomic controls. Macroeconomic control variables include Housing Price Index and unemployment rate. Robust standard errors appear in parentheses below the coefficients; * $p<0.1$; ** $p<0.05$; *** $p<0.01$.

	(1) Predicted probability of default	(2) Actual default dummy	(3) Prosper grade
Post-upgrade	0.0491***	0.0491***	0.0451***
	(0.00254)	(0.00431)	(0.00138)
Pr. default	0.821***		
	(0.00746)		
Post-upgrade *Pr. default	-0.153***		
	(0.00866)		
Actual default		0.0574***	
		(0.00323)	
Post-upgrade * Actual default		-0.0271***	
		(0.00340)	
Prosper grade			0.0472***
			(0.000132)
Post-upgrade *Prosper grade			-0.00729***
			(0.000157)
Amount borrowed (million)	-0.0897**	-4.527***	0.0631***
	(0.0370)	(0.0654)	(0.0221)
Cons	-0.0537***	0.117***	-0.143***
	(0.0204)	(0.0407)	(0.0113)
Macroeconomic controls	Yes	Yes	Yes
N	23,555	23,555	23,555
R^2	0.803	0.200	0.941

Appendix A. Proofs of Propositions

Proposition 1: Loan risk pricing is more sensitive to borrower risks under the auction mechanism than under the posted-price mechanism. Furthermore, the funding probability is lower under auctions than under the posted-price regime.

Proof: We note the Ith lowest break-even rate among N lenders as $r_I^{(N)}$. Under a posted price, Prosper will set loan rate R' to be the same as $r_I^{(N)}$, since a lower rate will not be sufficient to attract I investors, and a higher rate unnecessarily attracts more investors.

We now analyze the lender's optimal submission strategy under an auction mechanism. Let us first assume that all lenders j other than lender i submit $p_j = r_j$ and $j \in \{1, \ldots, i-1, i+1, \ldots, N\}$, and the $I-1$th and Ith lowest lending rates are $r_{I-1}^{(N-1)}$ and $r_I^{(N-1)}$, respectively. Now, we consider lender i whose break-even lending rate is r_i, according to his information, and who reports p_i. Lender i has no incentive to report $p_i < r_i$ since he will obtain a negative payoff if the loan originates and he is a lender or zero payoff if he is not involved or the loan does not originate.

We then analyze lender i's reporting strategy under three scenarios: $r_i \leq r_{I-1}^{(N-1)}$, $r_{I-1}^{(N-1)} < r_i < r_I^{(N-1)}$, and $r_i \geq r_I^{(N-1)}$. In the first scenario, lender i has no incentive to report $p_i < r_i$ since doing so does not affect whether the loan originates, which happens as long as $r_{I-1}^{(N-1)} \leq \bar{R}$, or to report loan rate $R = r_{I-1}^{(N-1)}$. However, he may have the incentive to report $r_i \leq r_{I-1}^{(N-1)} < p_i < min\left(r_I^{(N-1)}, \bar{R}\right)$ such that the loan rate becomes $p_i > r_{I-1}^{(N-1)}$, and the loan still originates.

Similarly, in the second scenario, lender i has no incentive to report $p_i < r_i$ because this may cause the lender to become involved in a loan at a rate p_i lower than his break-even level.

However, the lender still has an incentive to report $r_i < p_i < min\left(r_I^{(N-1)}, \bar{R}\right)$, which leads to a more profitable loan.

Finally, in the last scenario, the lender should not report $p_i < r_i$ because this may cause the lender to become involved in a loan at a lower rate than his break-even level. He should also not report $p_i > r_i$ because it does not change the outcome.

In summary, lender i should never report $p_i < r_i$, but he might overreport due to the possibility of $r_{I-1}^{(N-1)} < r_i < r_I^{(N-1)}$. In equilibrium, every agent has the same incentive to overreport their rates. Therefore, in the auction equilibrium, the borrower faces a rate of $R = p_I^{(N)} > r_I^{(N)} = R'$, where R$'$ is the rate under the posted-price regime, and $p_I^{(N)} - r_I^{(N)}$ increases with probability Pr $\{r_{I-1}^{(N-1)} < r_i < r_I^{(N-1)}\}$. Given that $F^B(r) > F^A(r)$ when borrower A is riskier than borrower B, the standard results in order statistics suggest that $Pr^A \left\{r_{I-1}^{(N-1)} < r_i < r_I^{(N-1)}\right\} > Pr^B \{r_{I-1}^{(N-1)} < r_i < r_I^{(N-1)}\}$. Hence, the premium of auction $p_I^{(N)} - r_I^{(N)}$ is higher for borrower A than for borrower B. In other words, the sensitivity of the interest rate to borrower riskiness is greater under an auction than under a posted-price auction.

Finally, given a borrower's maximum acceptable rate $\bar{R}$, by switching from auctions to posted prices, Prosper will be able to collect additional service fees from loans with $r_I^{(N)} < \bar{R} \leq p_I^{(N)}$. In other words, the funding probability under auction $Pr\left\{R = p_I^{(N)} \leq \bar{R}\right\}$ is lower than $Pr\left\{R' = r_I^{(N)} \leq \bar{R}\right\}$ or the funding probability under the posted-price regime.

Q.E.D.

Appendix B. Variable Definitions

Actual default	Indicator variable that equals one if a loan is actually defaulted and zero otherwise.
Amount borrowed	Borrowers' funded loan amount.
Amount delinquent	Dollar amount of the borrower's delinquent accounts.
Bankcard utilization	Percentage of available revolving credit utilized by the borrower.
Borrower rate	Borrowers' contract interest rates.
Credit history length	Number of months since the borrower's first recorded credit line at the time of loan origination.
Current credit lines	Number of current open credit lines.
Current delinquencies	Borrower's current number of delinquent accounts.
Delinquencies of last 7 years	Borrower's number of delinquent accounts of the past 7 years at the time the credit profile was pulled.
DTI with Prosper loan	Borrowers' debt-to-income ratio including Prosper loans.
Funding indicator	Funding indicator equal to one if a listing is funded and zero if a listing does receive funding.
Interest rate spread	Borrowers' posted interest rate or assigned interest rate minus corresponding daily treasury rate.
Listing amount	Borrowers' requested loan amount.
Loan spread	Borrower's loan interest rate minus corresponding daily treasury rate.
Group member	Indicator variable that equals 1 when the borrower is a Prosper group member and 0 otherwise.
Hazard rate	Expected number of loan defaults to occur at a particular time given that a default has not occurred yet.
Homeowner	Indicator variable that equals 1 when the borrower is a homeowner and 0 otherwise.
HPI	S&P/Case-Shiller US National Home Price Index.
Inquiries of last 6 months	Number of credit inquiries for the borrower made during the past six months.
P&L of investing	Ratio of the PV of payments received by the investor to the loan amount minus one.
Open credit lines	Number of borrower's currently open credit lines.
Post-switch	Indicator variable that equals 1 when Prosper.com has a posted-price market mechanism and 0 when Prosper.com has the auction market mechanism.
Prosper score	A custom risk score built using historical Prosper data that ranges from 1 to 11 with 11 being the best, or lowest risk, score and with 1 being the worst, or highest risk, score.
Pr. default	Predicted probability of default obtained using the

	logit model.
Public records of last 12 months	Borrower's number of public records from the past 12 months.
Public records of last 10 years	Borrower's number of public records from the past 10 years.
Revolving balance	Total outstanding balance that the borrower owes on open credit cards or other revolving credit accounts.
Stated monthly income	Borrower's self-reported income.
ScoreX score	Average of binned ScoreX score from Experian.
Total open revolving accounts	Total number of open revolving credit lines a borrower has.
Unemployment rate	Annual unemployment rate.

Appendix C. Additional Empirical Analysis

C.1 Alternative probability of default estimation

Our baseline empirical analysis is based on the probability of default estimation obtained using the credit performance of borrowers under both the auction and posted-price regimes, as the borrower's default probability, conditional on his profile, is unlikely to be altered retrospectively by the loan origination method.[25] Nevertheless, in this section, we offer a robustness check in which we estimate the probability of default using only the performance of loans funded under auction (from December 1, 2009 to November 30, 2010) and use the coefficients of this regression to predict the probability of default for the whole sample.

Specifically, we first estimate the probability of default using the auction subsample and obtain Pr. default (auctions) for each borrower and then repeat the regression of model (3):

$$\begin{aligned} Loan\ Spread_i = {} & \beta_0 + \beta_1 Postswitch_i + \beta_2 Estimated\ credit\ risk_i \\ & + \beta_3 Postswitch_i \times Estimated\ credit\ risk_i + \beta_4 Loan\ amount_i \\ & + Macroeconomic\ environment\ controls + \varepsilon_i \qquad (3) \end{aligned}$$

The results are reported in Table C.1. The evidence confirms the main finding that loan pricing is less sensitive to default risk after the pricing mechanism switch.

[25] In other words, if a P2P borrower who obtains a loan during the auction period defaults later, it is unlikely that the borrower could have avoided the default should he have acquired the loan during the posted-price regime and vice versa.

Table C.1 Sensitivity of Loan Spread to Default with the Probability of Default Estimated Using the Auction Subsample

Notes: This table presents the OLS regression results of loan spread on the postswitch dummy, the predicted probability of default obtained using the auction subsample, and its interaction with the postswitch dummy. The predicted probability of default is measured by unweighted logit regression. The loan spread is the borrower's contract interest rate minus the one-year daily treasury rate of the loan origination date. The postswitch dummy equals one when the loan is funded under posted pricing and zero when the loan is funded using auctions. Column (1) shows the unweighted regression result without borrower characteristics controls, and column (2) shows the unweighted regression result with controls. Column (3) shows the inverse propensity score weighted regression result without control variables, and column (4) shows the inverse propensity score weighted regression result with controls. Borrower characteristic controls are independent variables included in model (1). Other control variables include the loan amount, housing price index and unemployment rate. Robust standard errors appear in parentheses below the coefficients; * p<0.1; ** p<0.05; *** p<0.01.

	(1) Unweighted	(2) Unweighted	(3) IPS Weighted	(4) IPS Weighted
Post-switch	0.0505***	0.0321***	0.0591***	0.0372***
	(0.00348)	(0.00239)	(0.00332)	(0.00233)
Pr. default (auctions)	0.772***	0.644***	0.781***	0.648***
	(0.0126)	(0.0150)	(0.0111)	(0.0148)
Post-switch*Pr. default (auctions)	-0.267***	-0.233***	-0.280***	-0.247***
	(0.0143)	(0.00989)	(0.0131)	(0.00955)
Amount borrowed (million)	-1.718***	-0.665***	-1.990***	-0.866***
	(0.118)	(0.0959)	(0.115)	(0.0943)
HPI	0.000323	-0.000242	0.000245	-0.000490***
	(0.000249)	(0.000183)	(0.000247)	(0.000182)
Unemployment rate	-0.315	0.546***	0.0984	0.943***
	(0.260)	(0.191)	(0.257)	(0.188)
Cons	0.0561*	0.206***	0.0240	0.183***
	(0.0334)	(0.0315)	(0.0331)	(0.0311)
Borrower characteristics	No	Yes	No	Yes
N	13,380	13,380	13,380	13,380
R^2	0.610	0.779	0.618	0.782

C.2 Cox proportional hazard regression

Table C.2 Cox Proportional Hazard Regression

Notes: This table presents the Cox proportional hazard model estimates of default. The dependent variable is the number of months passed from the origination date of the loan to the default date if the loan defaults. The default date is replaced with the maturity date if the loan is fully paid off. The model can be expressed as

$$h_i(t) = [h_0(t)] \exp(b_0 + b_1 x_{i1} + b_2 x_{i2} + \ldots + b_n x_{in}) \qquad \text{(C.1)}$$

where h(t) is the hazard rate at time t; in our model, this is the likelihood that a loan will default. h_0 (t) is the baseline hazard at time t. x_i is the independent variable in the model. We report both coefficients and hazard rates. Standard errors appear in parentheses below the coefficients; * p<0.1; ** p<0.05; *** p<0.01.

	Coefficient	Hazard rate
DTI with Prosper loan	0.305***	1.357***
	(0.0748)	(0.101)
Homeowner	0.0250	1.025
	(0.0423)	(0.0434)
Group member	-0.325***	0.723***
	(0.0816)	(0.0590)
Years employed	-0.00125	0.999
	(0.00264)	(0.00264)
Stated monthly income (thousand)	-0.0230***	0.977***
	(0.00723)	(0.00706)
Amount delinquent (thousand)	-0.00131	0.999
	(0.00249)	(0.00249)
Bankcard utilization	-0.328***	0.721***
	(0.0639)	(0.0460)
Current credit lines	-0.0296***	0.971***
	(0.00428)	(0.00415)
Current delinquencies	0.0400***	1.041***
	(0.0128)	(0.0133)
Credit history length	0.00853***	1.009***
	(0.00260)	(0.00263)
Revolving balance (million)	0.633	1.883
	(0.654)	(1.232)
Delinquencies of last 7 years	-0.00544**	0.995**
	(0.00215)	(0.00214)
Public records of last 10 years	0.0403	1.041
	(0.0272)	(0.0284)
Public records of last 12 months	-0.00400	0.996
	(0.122)	(0.122)
Inquiries of last 6 months	0.0621***	1.064***
	(0.0109)	(0.0116)
ScoreX score (thousand)	-0.00187***	0.998***
	(0.000561)	(0.000560)
Prosper score	-0.0291*	0.971*
	(0.0150)	(0.0146)
Prosper grade A	1.057***	2.879***
	(0.183)	(0.528)
Prosper grade B	1.427***	4.167***
	(0.184)	(0.766)
Prosper grade C	1.444***	4.238***

	(0.191)	(0.809)
Prosper grade D	1.857***	6.405***
	(0.185)	(1.184)
Prosper grade E	2.075***	7.968***
	(0.196)	(1.564)
Prosper grade HR	1.979***	7.235***
	(0.204)	(1.478)
N	13,380	13,380

Appendix D. Sample Loan Request

The following sample loan request can be found at https://www.prosper.com/published/sec/listing/2010/listing 20101201-1424.htm

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Borrower Payment Dependent Notes Series 486150

The following information pertains to the borrower loan being requested, that corresponds to the series of Notes to be issued upon the funding of the borrower loan, in the event the listing receives commitments to purchase Notes in an aggregate amount of the requested loan.

Amount:	**$7,000.00**	Prosper Rating:	**B**	Auction Duration:	**7 days**
Term:	**36 months**	Estimated loss:	**4.95%**		
Starting lender yield:	**10.87%**	Starting borrower rate/APR:	**11.87% / 14.00%**	Starting monthly payment:	**$232.07**
Auction yield range:	**5.57% - 10.87%**	Estimated loss impact:	**5.13%**		
Lender servicing fee:	**1.00%**	Estimated return:	**5.74%**		

The Estimated Return is presented to help you evaluate this listing and set an appropriate minimum yield and bid amount. Estimated Return is the average annual expected return on funds invested in this loan and is calculated by subtracting the estimated impact of credit losses on the loan from the minimum yield. The estimated impact of credit losses is derived from the following components: The estimated average annualized loss rate based on the historical performance of Prosper loans for borrowers with similar characteristics, originated between Apr-01-2007 and Mar-31-2008, measured as of Mar-31-2009, and an adjustment for accrued interest not collected and late fees on defaulted loans.The Estimated Return presented does not assume any early repayment by the borrower. The calculation of Estimated Return requires significant assumptions about the repayment of the loan and lenders should make their own judgments with respect to the accuracy of these assumptions. Actual performance may differ from estimated performance.

Borrower's Credit Profile

Prosper score (1-10):	**8**	First credit line:	**Dec-1995**	Debt/Income ratio:	**12%**
Credit score:	**780-799 (Nov-2010)**	Inquiries last 6m:	**1**	Employment status:	**Employed**
Now delinquent:	**0**	Current / open credit lines:	**8 / 3**	Length of status:	**3y 6m**
Amount delinquent:	**$0**	Total credit lines:	**29**	Occupation:	**Engineer - Mechanic...**
Public records last 12m / 10y:	**0/ 0**	Revolving credit balance:	**$1,404**	Stated income:	**$75,000-$99,999**
Delinquencies in last 7y:	**0**	Bankcard utilization:	**31%**		
		Homeownership:	**Yes**		
Screen name:	**first-worldly-affluence**	Borrower's state:	**NewJersey**	Borrower's group:	**N/A**

Credit and homeownership information was obtained from borrower's credit report and displayed without having been verified. Employment and income was provided by borrower and displayed without having been verified.

Prosper Activity

Loan history		**Payment history**		**Credit score history**
Active / total loans:	**0 / 1**	On-time:	**9 (100%)**	780-799 (Latest)
Principal borrowed:	**$9,000.00**	< 31 days late:	**0 (0%)**	
Principal balance:	**$0.00**	31+ days late:	**0 (0%)**	720-739 (Dec-2009) 740-759 (Nov-2009)
Total payments billed:	**9**			

Description

WEDDING LOAN

Purpose of loan:
This loan will be used for?my upcoming wedding.

My financial situation:
I am a good candidate for this loan because I currently have a great job as a civil engineer that provides steady income for my family. In this economy I feel very fortunate to have a career with plenty of job security. I have a long bright future with my current company.? Based on my history I?m a successful prosper borrower.? My record shows that all payments were made on time and I was actually able to pay the loan off earlier than expected.

Information in the Description is not verified.

Note: The original online sample loan request contains some TYPOs.