FinTech Isn't So Different from Traditional Banking: Trading off Aggregation of Soft Information for Transaction Processing Efficiency

Abstract: We examine trade-offs that Prosper, a large online peer-to-peer lending platform, has made over time in its lending processes. Since its 2006 inception, Prosper has (1) changed the way it sets the interest rates on loans from auctions among peer lenders to pre-set pricing based on a proprietary credit-rating model in December 2010; (2) enabled institutional investors to fund whole rather than just fractional loans in April 2013; and (3) reduced the extent of soft information available to peer lenders in September 2013. In each of these changes, Prosper has traded off the aggregation of soft information by peer lenders for transaction processing efficiency, a trade-off similar to that made by large traditional banks. We provide the following evidence regarding the costs and benefits of this trade-off. On the cost side, after the December 2010 change the distribution of loan interest rates shrinks and the ability of interest rates to predict loan default deteriorates, particularly for loans to low credit quality borrowers for whom soft information is more important for credit screening. After the April 2013 change interest rates for low credit quality loans in the fractional loan market are more predictive of default than are interest rates in the whole loan market. On the benefit side, loan volume and funding speed rise sharply after each of these changes. Moreover, the costs appear manageable, as peer lenders' ability to diversify increases and the weighted-average interest rate of a modest-size portfolio of Prosper loans remain just as predictive of default. Placebo and difference-in-differences tests using a peer-to-peer lender that did not change its lending processes during our sample period (Lending Club) indicates that these effects are attributable to the changes in Prosper's processes.

Keywords: soft information; peer-to-peer lending; credit screening; transaction processing efficiency.

1. Introduction

Since the early 2006 launch of the first online peer-to-peer lending platform in the U.S., Prosper Marketplace Inc., ("Prosper"), the peer-to-peer lending industry has experienced tremendous growth and change. The industry began by matching small retail borrowers to non-institutional lenders, who could read loan applicants' personal narratives and ask them questions before funding loan requests (referred to as the "democratization of finance" by Shiller 2009 and others). The industry now serves a broader range of borrower and particularly investor types, with most loans being funded by institutional investors such as banks (referred to as "reintermediation" by Balyuk and Davydenko 2018). To facilitate this evolution, the industry has streamlined its information environment and lending processes. Today, most platforms provide few if any channels for loan applicants to provide soft information. Loan requests can be funded within seconds of being listed on platforms by institutional investors' automated investment algorithms.

In this study, we provide quantitative evidence of the informational costs and transaction processing efficiency benefits of three major changes in its processes that Prosper has made since its inception to effect or respond to the evolution of the peer-to-peer lending industry. First, in December 2010 Prosper changed the way in which interest rates are determined, moving from auctions among peer lenders with access to both hard and soft information about borrowers (the auction regime) to a proprietary credit-rating model based on hard information (the pre-set pricing regime). Second, in April 2013 Prosper created a whole loan channel that caters to institutional investors and is separate from the preexisting fractional loan channel attractive to retail investors; relatedly, in November 2013 it created a whole loan channel that allows passive investment by institutional investors based on pre-specified criteria. Third, in September 2013 Prosper eliminated the ability of loan applicants to provide soft information through descriptions of their life circumstances and intended loan purposes ("loan descriptions"). Each of these changes trades off the aggregation of soft information by peer lenders in favor of the speed and volume of transaction processing. This trade-off is very similar to the one made by large traditional banks in emphasizing hard rather than soft information (Berger and Udell 2002).

We examine how this reduced incorporation of soft information affects the informational efficiency of loan interest rates, in particular, their variance and ability to predict default. Soft information should help predict default on retail loans owing to "the complexities and idiosyncrasies of human behavior," which render default "not just the result of a mechanical financial calculus" (Iyer et al. 2016). Prior research finds that soft information, while typically unverifiable, improves lenders' decision making, particularly for credit risky borrowers (Petersen and Rajan 1994, Duarte et al 2012, Michels 2012, Freedman and Jin 2014, Iyer et al. 2016). Despite these benefits, large traditional banks typically find that the costs of collecting and processing soft information, compared to the inexpensive and verifiable alternative of hard information, exceed the benefits for relatively small-balance consumer loans (Berger and Udell 2002). By shifting these costs to peer lenders more willing or able to bear them, peer-to-peer lending platforms can outcompete traditional banks in funding these loans.

In the auction regime prior to December 2010, Prosper posted on its platform loan applicants' hard information, such as credit score buckets, debt-to-income ratios, and recent credit inquiries, as well as soft information, such as loan descriptions. Prosper conducted auctions in which individual investors decided based on this information whether and at what interest rates to bid to fund portions of the loan requests. If the total bids submitted in an auction equaled or exceeded the requested amount, the loan was originated at the interest rate bid by the marginal successful investor. Research shows that non-expert peers perform fairly well in selecting and pricing loans using the available hard and soft information (see Morse 2015 for a review). For example, for the loans originated by Prosper in 2007 and 2008, Iyer et al. (2016) find that during the auction regime Prosper's peer lenders collectively achieved 87% of the accuracy in predicting defaults of an econometrician who observes all standard borrower characteristics and loan terms, some of which are unobservable to peer lenders.

In the pre-set pricing regime after December 20, 2010, Prosper determines interest rates based on its proprietary credit ratings. After loan applicants fill in basic personal information and loan terms (amount and maturity), Prosper obtains the applicants' credit reports, determines their credit ratings, and sets the interest rates. If an applicant accepts the offered rate, the loan terms and the applicant's credit profile and any loan description are posted on Prosper.com.[1] Lenders evaluate this information and decide whether to fund a portion of the loan request.

Consistent with the December 2010 regime change largely eliminating the soft information in loan interest rates, we find that that the distribution of loan interest rates within each credit rating category shrinks after the December 2010 change, more so for borrowers with lower creditworthiness for whom soft information is more important for credit screening. Because the shrinkage in the distribution does not necessarily indicate less informationally efficient interest rates, following Iyer et al. (2016) we examine the ability of interest rates to predict loan default, as evidenced by the area under the receiver operating characteristic curve (AUC). A higher AUC indicates interest rates have a higher predictive power for default. For funded loans that are listed before the December 2010 regime change, we find the AUC is 0.67, similar to that reported by Iyer et al. (2016). After the regime change, the AUC falls to 0.63-0.64;

[1] Thus the pre-set pricing regime discourages loan applicants unwilling to accept the interest rate offered without posting the applicants' information on its platform. We do not have information on loan requests that have never been posted on Prosper.com, but Lending Club (LC) provides the complete set of loan requests, posted or not. During our sample period, 1,910,012 requests are made at LC, of which only 403,810 (21.1%) are posted according to its Form 424B3 filed with the SEC.

this drop is statistically and economically significant and driven by lower credit quality loans, consistent with it being attributable to the loss of soft information.

To identify the extent and impact of soft information, we examine whether the length and detail of loan descriptions are associated with the drop in the predictive power of interest rates for loan default. We find that lower credit quality loans with longer or more detailed loan descriptions have a significantly higher predictive power for default under the auction regime prior to December 2010, but not subsequently under the pre-set pricing regime. Moreover, we find that the R^2s of regressions of interest rates on loan applicant characteristics and loan terms are stable or increase around December 2010, indicating that the interest rates incorporate at least the same amount of hard information. This evidence is consistent with the loss of soft information explaining the reduced predictive power of interest rates for default after December 2010. Our findings contribute to prior studies that focus on the benefits of increasing loan volume and funding speed (Morse 2015; Wei and Lin 2016).

We attempt to rule out two alternative explanations for our findings. One alternative is that the drop in the predictive power of interest rates for default over time is the result of an increase in borrower risk, which may be either observable or unobservable. We conduct three analyses to rule out this possibility. First, we examine changes in *observable* borrower characteristics (e.g., credit score) from before to after December 2010, and find that these characteristics are stable or even improve. Second, we compare the predictive power of interest rates for loans that Prosper assigns the same credit rating based on available hard information, and find that the predictive power of interest rates for default deteriorates in each credit rating category below B. Third, we examine trends in the predictive power of interest rates for default prior to December 2010. If borrower risk changes gradually and unobservably over time, say because borrower diversity increases as Prosper grows, this predictive power should deteriorate prior to December 2010. When we split the auction regime subperiod into early and late parts, however, we find no significant change in the predictive power of interest rates. These analyses suggest that the decrease in the predictive power of interest rates around the regime change in December 2010 is not driven by changes in borrower risk.

The other alternative is that the drop in the predictive power of interest rates is attributable to uncertainty about the macroeconomy or other economic variables that affect peer-to-peer borrowers. To test this possibility, we examine the informational efficiency of interest rates of Prosper's major competitor, Lending Club ("LC"), whose clientele is similar to Prosper's, and which also enjoyed a spectacular growth like Prosper over our sample period. Since its inception in 2007, LC has set interest rates using its own proprietary credit-rating model. We find that the distribution of interest rates set by LC expands rather than shrinks over time, and the predictive power of LC's interest rates for loan default does not decrease for both good and poor credit quality loans. These results of this placebo test suggest that changes in economic conditions do not explain the deterioration in the predictive power of interest rates set by Prosper after December 2010.

To identify the benefits of the three changes, we conduct difference-in-differences tests of Prosper's changes in loan application and origination volume and loan origination delay around the three changes in its lending processes using LC's loan applications and originations as the control group. We find that these policy changes improved the speed and volume of transaction processing at Prosper and thus increased the ability of lenders to diversify idiosyncratic credit risk. These findings imply that Prosper's lenders do not necessarily bear more risk under the pre-set pricing regime, despite the decreased informational efficiency of

Prosper's interest rates. To explore this possibility, we examine the ability of the value-weighted average interest rates of portfolios of 5, 10, or 20 randomly selected loans with the same credit rating issued around the same time to predict default and the proportion of unpaid principal. We detect no deterioration in this ability for even modest-size portfolios.

Our study contributes to two primary strands of literature. First, our finding that Prosper forgoes benefits from the use of soft information in setting interest rates to facilitate transaction processing efficiency contributes to the literature that shows how FinTech has led to (1) increased reliance by traditional banks on hard information in credit screening and monitoring (Liberti and Petersen 2017), (2) efficiency and growth in various loan markets (Einav et al. 2013 re auto lending, Filomeni et al. 2016 re corporate lending, and Buchak et al. 2017 re residential mortgage lending), and (3) reintermediation in peer-to-peer lending (Balyuk and Davydenko 2018). Second, our finding that the informational efficiency of loan interest rates falls when Prosper switches from the auction regime to the pre-set pricing regime contributes to findings in FinTech and other areas of the "wisdom of the crowd", i.e., that groups of non-experts often make judgments that are equally good or informationally incremental to those of experts (Arrow et al. 2008, Jame et al. 2016, Mollick and Nanda 2016, Lin et al. 2017). Relatedly, this finding contributes to the large banking literature that shows the importance of soft information in credit screening and monitoring (Berger and Udell 2002).

Related to both of these strands, our findings contribute to Michels (2012) and Netzer et al. (2016), studies that conduct textual analysis of loan descriptions and show that the conveyance and use of soft information by peer-to-peer borrowers and lenders, respectively, can yield substantial reductions in information asymmetry and loan interest rates. More generally, similar to a contemporaneous study by Balyuk and Davidenko (2018) that focuses on reintermediation of banks in peer-to-peer lending, our study responds to Morse's (2015) call for more research on "the optimality of the [peer-to-peer] lending structure", providing an up-to-date evaluation of the pricing efficiency of a major peer-to-peer lending platform that should inform regulators and practitioners about the quality of credit screening in peer-to-peer lending.

The rest of the paper is organized as follows. Section 2 discusses peer-to-peer lending and Prosper in detail. Section 3 describes our sample and data. Section 4 develops the empirical models and reports the empirical analyses. Section 5 concludes.

2. Background and Sample Period

An online peer-to-peer lending platform matches loan applicants who seek loan funds with lenders who seek to invest in loans. Prosper launched the first U.S. platform in early 2006. Although still in its infancy, the peer-to-peer lending industry has enjoyed tremendous growth since 2006. The industry reached annual loan issuance of $5.5 billion in 2014 from zero in 2006, according to PWC (2015). Goldman Sachs (2015) estimates that among the $843 billion of unsecured personal loans outstanding in the U.S. as of the end of 2014, $258 billion of that amount is "addressable" by peer-to-peer lending platforms, and that they would collectively hold a 9% share of that market by 2020 if they maintain their current growth rates.

We focus on Prosper for three main reasons. First, Prosper is the second largest peer-to-peer lending platform in the U.S., which ensures a representative sample of peer-to-peer loans. Second, as described in the introduction Prosper has made significant changes in its information environment and lending processes over time, enabling us to study the costs and benefits of these changes. Third, to date Prosper has only issued unsecured personal loans with fixed interest rates and relatively stable other loan contractual terms. Specifically, loan amounts initially are from $1,000 to $25,000, with the maximum eventually rising to $35,000. Loan maturities initially are

1, 3, or 5 years, with 1-year maturities eventually eliminated. Borrowers are required to make monthly loan payments. Prosper retains a 1–3% origination fee and a 1% servicing fee and transfers the remaining loan payments to lenders. Hence, the effects of the changes in Prosper's information environment and lending processes that we document are unlikely to be attributable to changes in its loan composition or terms over time.

Figure 1 depicts the timeline of the three key changes in Prosper's lending processes described in the introduction. These changes divide our August 2009 to February 2014 sample period into four subperiods. The sample period begins in August 2009 because in November 2008 the SEC issued an order for Prosper to cease and desist from selling unregistered securities collateralized by loans, which caused Prosper to stop new lending. Prosper registered with the SEC in July 2009 and resumed lending. The sample period ends in February 2014 because we are only able to match the loan requests posted on Prosper's lending platform (referred to as "listings") to the subsequent performance of the corresponding funded loans.[2] We obtain performance data for these loans through November 2017.

Subperiod 1 covers loan listings from August 2009 to December 19, 2010. During this subperiod, Prosper employed a reverse auction model in which loan applicants posted their loan requests on the Prosper.com platform indicating the dollar amount requested and the maximum interest rate they are willing to pay up to a maximum of 36%, and providing basic credit information and possibly loan descriptions and other soft information.[3] Interested investors submitted irrevocable bids indicating the dollar amounts they would fund (from a minimum of $25 to a maximum that initially was 75% of the requested loan amount and fell over time) and

[2] Specifically, Prosper provides two separate datasets with distinct identifiers for loan listings and originated loan performance. To merge these datasets, we use an old vintage of the data (downloaded from https://s3.amazonaws.com/udacity-hosted-downloads/ud651/prosperLoanData.csv) that links the two loan identifiers for loans originated up to February 2014.

[3] The description of Prosper's processes during subperiod 1 is based on its July 13, 2009 Form S-1/A filing.

the minimum interest rates they would accept (down to a floor dependent on the credit rating of the loan request). If at the end of the bidding process the total loan amounts bid equaled or exceeded the requested amount, the loan application was offered to be funded by the bids with the lowest interest rates sufficient to fund the requested amount, and the interest rate was set at the highest interest rate of the funding bids; otherwise, the loan request expired (typically after 7 days). Throughout our sample period, at any time prior to loan origination loan applicants can withdraw their listings and Prosper can also cancel loan applications if it detects identity or other fraud or loan applicants fail to provide required documents.

Subperiod 2 covers loan listings from December 20, 2010 to April 11, 2013. During this period, Prosper set interest rates using a proprietary credit-rating model that incorporated only loan applicant characteristics and loan terms.[4] According to Prosper's founder and then CEO, Chris Larsen, this change in how interest rates are set from the prior auction approach benefitted lenders and borrowers by "simplifying and speeding up the process of funding loans."[5] Peer lenders decided whether to fund a portion of the loan request at the interest rate set by Prosper. Along with this change in how interest rates are determined, other changes made by Prosper at the same time include (1) allowing partial funding of loan requests that receive total bids of at least 70% of the requested loan amount; (2) increasing the maximum bidding period from 7 days

[4] This change, along with other changes discussed later in the paragraph, is described in Prosper's December 17, 2010 POS AM filing. Prosper indicates that it sets loan interest rates based on borrowers' Prosper Ratings as well as additional factors such as "loan terms, group affiliations, competitive conditions and the general economic environment". Prosper Ratings take seven possible letter values (AA, A, B, C, D, E, and HR) that correspond to ranges of estimated average loss rates. The base loss rate is "based on the historical performance of Prosper borrower loans with similar characteristics and is primarily determined by two scores: (1) a custom Prosper score, discussed below, and (2) a credit score obtained from a credit reporting agency (currently, the Scorex PLUS score from Experian)." "Adjustments can be made to the base loss rate based on variables such as the presence of a previous Prosper loan." The custom Prosper score ranges from 1 to 10, computed by adding weights assigned to ranges of categorical variables for the predictors included in the proprietary scorecard model. The primary predictors are "inquiries in total and in the last 6 months, trades in total and in the last 6 months, trades never delinquent or derogatory, trades with delinquent balances, available credit on open bankcards, debt-to-income ratio, and bankcard utilization".

[5] December 20, 2010 Prosper press release https://www.businesswire.com/news/home/20101220005317/en/Prosper-Reports-17-Increase-Loans-November.

to 14 days; and (3) terminating bidding as soon as sufficient bids are obtained to fully fund the requested maximum loan amount.[6] Notably, the credit information provided by loan applicants did not change on December 20, 2010.

Subperiod 3 covers loan listings from April 12, 2013 to September 5, 2013. At the beginning of this period, Prosper launched a whole loan program in which it randomly allocated loan requests to the whole loan channel.[7] Institutional investors and accredited individual investors primarily participate in the whole loan channel, funding the entire loan request. Loans not allocated to the whole loan channel remain in the fractional loan channel to be funded primarily by retail investors using the same approach as in subperiod 2. If a loan request allocated to the whole loan channel is not funded after the bidding period, it is reallocated to the fractional channel. Around this time, Prosper eliminated 1-year maturity loans and increased the maximum loan size from $25,000 to $35,000 for loans with Prosper credit ratings of AA, A, and B.[8] In November 2013, Prosper added a distinct whole loan channel that allows institutional investors to passively invest in whole loans based on pre-set criteria for on standard credit variables.

In subperiods 1 through 3, loan applicants could, but were not required to, provide descriptions of their life circumstances and intended loan purposes. Prosper emphasized that it did not verify the information in these loan descriptions. In subperiod 1, almost every loan applicant provided a loan description, although the length and detail of the descriptions varied considerably across applicants. Reflecting the elimination of the use of soft information in setting

[6] Our results are robust to excluding 7,489 originated loans listed in subperiods 2-4 that took over 7 days to be funded.

[7] This change is discussed as occuring in April 2013 in Prosper's August 12, 2013 10-Q filing. April 12, 2013 is the first day that the variable *investment_typeid* in the Prosper data takes the value of whole loan.

[8] Our results are robust to excluding loans with loan amounts above $25,000 issued in subperiods 3 and 4.

interest rates in subperiod 2, only 77.1% of loan requests (80.2% of issued loans) provided loan descriptions during subperiod 2, and only 68.7% (70.6%) provided them in subperiod 3.

Subperiod 4 covers loan listings from September 6, 2013, when Prosper eliminated loan applicants' ability to provide loan descriptions, to February 28, 2014, the end of our sample period.[9] The then President of Prosper Funding, LLC, Aaron Vermut, indicates that Prosper made this change to simplify the loan application process and increase the likelihood that borrowers complete loan applications.

Figures 2 to 4 depict Prosper's evolution. Figure 2 shows that Prosper's loan requests and loan issuance grew substantially from its initiation in 2006 to the third quarter of 2017, albeit with dips in late 2008 (owing to the SEC cease-and-desist order), the fourth quarter of 2012 (for reasons not apparent to us), and the first three quarters of 2016 (owing to slowing credit supply, a potential downgrade for securities backed by Prosper loans, and scrutiny of its lending to the San Bernardino shooter, respectively).[10]

Figure 3 depicts the increase in Prosper's average funding rate (funding commitment per listing scaled by the borrowing amount requested) over time. The average funding rate is below 20% in subperiod 1, increases substantially during subperiods 2 and 3, and is well over 90% in subperiods 3 and 4. While some portion of this increase likely is attributable to Prosper's ability

[9] This change is discussed, and the quote from Aaron Vermut in the next sentence appears, in the online forum https://forum.lendacademy.com/index.php?topic=1561.30. This change is also evident from the drop in the number of loan requests with narrative descriptions from 68 on September 5, 2013 to 7 on September 6, 2013 and to zero by September 28, 2013. Our inferences are unaffected if we instead use September 27/28, 2013 as the dividing line between subperiods 3 and 4.

[10] These interpretations are evident in Andriotis and Demos, "Prosper Shuts Off Borrowers From Two Loan-Marketing Sites: Online lender works to find more investor capital as it slows courting of new borrowers", *The Wall Street Journal*, June 8, 2016 https://www.wsj.com/articles/prosper-shuts-off-borrowers-from-two-loan-marketing-sites-1465402174, Moody's, "Moody's places on review for downgrade marketplace lending ABS issued by Citi Held for Asset Issuance", *Moody's Rating Action*, February 11, 2016 https://www.moodys.com/research/Moodys-places-on-review-for-downgrade-marketplace-lending-ABS-issued--PR_343705, Delamaide, "Loan to terror couple challenges regulators", *USA Today*, December 15, 2015 https://www.usatoday.com/story/money/2015/12/15/shooting-terrorism-online-loans-san-bernardino/77358520/

to discourage loan requests by setting interest rates up front, the increase from subperiod 2 to subperiods 3 and 4 suggests that peer lenders' supply of capital also strongly increased.

We define the time to funding as the elapsed time from when Prosper posts the loan request on its platform to the end of the bidding period (which occurs after 7 days in subperiod 1 and after the earlier of the receipt of sufficient bids to fully fund the loan request and 14 days in subperiods 2-4). Figure 4 shows that the average time to funding for successful loan requests decreases sharply with each successive subperiod. Time to funding drops from over 100 hours during subperiod 1 to about 10 hours in subperiod 4. The drop is mainly driven by loans funded by institutional investors.

3. Data

We obtained two datasets from Prosper.com on November 12, 2017 (the "data download date").[11] The listing dataset contains the following data for loan requests: (1) loan applicant characteristics (e.g., debt-to-income ratio) and credit scores in 11 buckets with width of at least 15 points;[12] (2) requested loan amount and maturity; (3) funding outcomes, such as the funding commitments by lenders and the time to funding; (4) the interest rate, which is a funding outcome in subperiod 1 and set by Prosper in subperiods from 2 to 4; and (5) the final statuses of loan listings, which take four possible values (completed, canceled by Prosper, withdrawn by loan applicants, or expired because the total funding commitments at the end of the bidding period is below the required minimum for funding).[13]

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[11] We download the data for Prosper from https://www.prosper.com/investor/marketplace#/download.

[12] Prosper primarily used Experian ScoreX PLUS in subperiods 1 through 3 and TransUnion FICO in subperiod 4. The listing dataset continues to include Experian ScoreX PLUS in subperiod 4, however. Untabulated comparisons indicate that Experian ScoreX PLUS is more conservative than TransUnion FICO. For example, 94.7% of the borrowers with Experian ScoreX PLUS below 640 have a TransUnion FICO score above 640.

[13] The bidding period (maximum time listed on Prosper's platform) is 7 (14) days in subperiod 1 (subperiods 2–4). The required minimum for funding is 100% of the requested loan amount in subperiod 1 and 70% (100%) of that amount for borrowers that have (have not) selected partial funding in subperiods 2–4.

The loan performance dataset contains a snapshot of borrowers' repayment histories as of the data download date for funded loans. We also obtained loan descriptions by scraping the Prosper's Form 424B3 (prospectus supplements for the borrower payment dependent notes) filings to the SEC. Appendix A contains definitions of all of the variables used in the empirical analysis. Appendix B reproduces a sample loan request from a Form 424B3 filing.

Our sample period begins in August 2009, the first full month after Prosper registered with SEC, and ends on February 28, 2014. Our sample includes all loan requests and funded loans in the two datasets except for those with 1-year maturity (2,605 loan requests, of which 1,613 are funded)[14] or missing required data (119 loan requests, of which 44 are funded). As discussed in Section 2, we split the sample period into four subperiods.

Table 1 provides summary information about the sample listings during each of the four subperiods. Panel A reports the means and standard deviations of loan applicant characteristics and loan terms. The loan terms suggest that peer lenders' credit supply and risk tolerance increase over time. The average interest rate falls monotonically from 24.6% in subperiod 1 to 16.6% in subperiod 4. The average requested loan amount rises monotonically from $7,067 in subperiod 1 to $11,824 in subperiod 4. The average funding rate (total funding commitment scaled by the requested loan amount) rises monotonically from 28.8% in subperiod 1 to 95.5% in subperiod 4.

The loan applicant characteristics appear fairly normal given the applicants' apparent willingness to accept fairly high (credit card-like) interest rates. Approximately half of loan applicants own homes and 80% or more are employed. Loan applicants have an average of between 8 and 11 current open credit lines and from 0.20 to 0.44 current delinquencies.

[14] We delete loans with 1-year maturity because Prosper stopped offering these loans in subperiod 3.

Reflecting the declining provision of soft information, the likelihood that loan applicants provide loan descriptions falls monotonically from essentially 100% in subperiod 1 to 68.7% in subperiod 3, before being disallowed in subperiod 4.[15] Similarly, the likelihood that loan applicants have group affiliations (engage in social networking on Prosper's platform) falls from 7.1% in subperiod 1 to 0.7% in subperiod 4.[16] The percentage of loan requests from applicants that have previously received loans from Prosper falls monotonically from 45.4% in subperiod 1 to 17.2% in subperiod 4, reflecting Prosper's growth and increasing acceptance from borrowers. In subperiod 3, Prosper allocates 53.1% (46.9%) of loan requests to the fractional (whole) loan market. In subperiod 4, the percent of loan requests that Prosper allocates to the whole loan market rises to 66.7% (38.9% to the active market and 27.8% to the passive market).

Table 1, Panel B reports the frequencies of the four possible outcomes of loan requests reported by Prosper: (1) "Cancelled", (2) "Completed", (3) "Expired" without being offered the required minimum amount by the end of the bidding period, and (4) "Withdrawn" by the loan applicant. In the over 16-month subperiod 1, loan applicants make 41,706 loan requests (83 per day), of which 17.8% are funded (in full), 3.9% are canceled, 41.8% expire, and 36.5% are withdrawn. In the over 28-month subperiod 2, loan applicants make 62,870 loan requests (75 per day); this slightly lower rate of requests per unit time than in subperiod 1 is likely attributable to interest rate shopping and application withdrawal after interest rates are assigned before their requests are posted in subperiod 2 (see footnote 1). Reflecting the regime switch and to a lesser extent borrowers' interest rate shopping and ability to partially fund loans, the percentage of loan

[15] These loan description statistics are for listings allocated to the fractional loan channel. As mentioned above, we obtain loan descriptions by scraping SEC Form 424B3 filings (prospectuses for borrower payment dependent notes). Because whole loans are not considered to be securities (Securities Act of 1933), Prosper is not required to and does not list whole loans in the prospectuses, so we do not have information on the descriptions of listings and loans in the whole loan channel.

[16] 94% (73%) of applicants with group affiliations have previously requested (received) loans.

requests funded in full or part rises sharply to 53.8%, and the percentages of requests that expire or are withdrawn fall sharply to 9.0% and 13.9%, respectively. The percentage of requests that Prosper cancels rises sharply to 23.2%. The reason for this increase is unclear to us. We determined that it is not attributable to the cancelation rate differing for fully and partially funded loans. It may be that over time, as peer lenders become increasingly comfortable with searching for yield and/or with Prosper's credit evaluation and verification processes, Prosper exercises relatively more discipline over the lending process. This possibility is consistent with Balyuk and Davydenko's (2018) observation that institutional lenders increasingly outsource lending decisions to peer-to-peer lending platforms.

The number of loan requests is 19,266 (131 per day) in the almost 5-month subperiod 3 and 45,768 (260 per day) in the almost 6-month subperiod 4; the number of requests per unit time increases sharply from subperiod 2 to subperiod 4, reflecting Prosper's growth. The percentages of the four possible outcomes of loan requests change more moderately from subperiod 2 to subperiod 4; the percentages completed and canceled rise further, to 59.3% and 36.2%, respectively, while the percentages expired and withdrawn fall further, to 0.1% and 4.4%, respectively.

Table 1, Panel B also reports the frequencies of the 11 loan applicant credit score buckets. Loan applicants fall in a wide range of credit score buckets from a solidly subprime level of 600 to a solidly prime level of over 778. Perhaps surprisingly, the median credit score is slightly below (above) 700 in subperiod 1 (subperiods 2–4), low to middle prime levels.

Finally, Panel B reports the frequencies of the intended loan purposes reported by loan applicants and not verified by Prosper. Debt consolidation is by far the most frequent loan purpose in all subperiods, and it becomes significantly more common in the later subperiods, rising from 46.9% of listings in subperiod 1 to 77.3% in subperiod 4. Home improvement, business, auto/motorcycle/RV/boat, and other are reasonably common loan purposes. In subperiod 2, Prosper removed the student use loan purpose and added 13 new loan purposes; this explains the zeros in subperiod 1 for the new loan purposes and in subperiods 2–4 for student use.

Following the same structure as Table 1, Panel A of Table 2 provides summary information about the funded loans during each of the four subperiods. Panel A reports the means and standard deviations of a default indicator, the unpaid principal amount, the loan terms, the loan applicant characteristics, the number of investors funding the loan, and the time to funding. The average percentage of loans that default increases from 16.5% in subperiod 1 to 23.2% in subperiod 2, before falling to 17.2% in subperiods 3 and 4. Similarly, the average percent of the unpaid principal as of the end of our loan performance data in November 2017 is lowest in subperiod 1 (10.l%) and highest in subperiod 2 (15.5%). Comparison of average loan terms and loan applicant/borrower characteristics in Panels A of Tables 1 and 2 shows that funded loans are on average considerably less risky than loan requests in subperiod 1. For example, funded loans have 3.8% lower interest rates, 0.16 lower current delinquencies, 4% lower debt-to-income ratios, and an 8.7% higher likelihood of an employed borrower. These differences diminish over time and are essentially eliminated by subperiod 4, again suggesting that lenders' risk acceptance increases over time. Reflecting the creation of the whole loan channel in subperiod 3 and other factors, the average number of investors per loan falls from 138.0 in subperiod 1 to 32.1 in subperiod 4. Reflecting Prosper's switch to the pre-set pricing regime in subperiod 2 and other factors, the average time to funding falls from 148.9 hours in subperiod 1 to 5.4 hours in subperiod 4.

Table 2, Panel B reports the frequencies at the November 12, 2017 data download date of the four loan performance statuses reported by Prosper: “ChargeOff” at 120 days past due; “Defaulted”, which includes subcategories for bankruptcy, death, and various forms of settlements with borrowers; “Current”, defined as less than 120 days past due; and “Completed.” As the sample loans all have terms of 5 years or less, and subperiod 4 ends on February 28, 2014, only 5.7% of loans remain current at that date. Almost all current loans were listed in subperiods 3 and 4. Overall, loan performance is reasonably stable across subperiods, with subperiod 2 exhibiting somewhat worse performance than the other subperiods. For example, the sum of charged-off and defaulted loans is 16.5%, 23.2%, 17.1%, and 17.1% in subperiods 1 through 4, respectively.

Table 2, Panel B also presents the distributions of the credit score buckets and reported loan purposes for funded loans. The credit score buckets again indicate that on average funded loans are considerably less risky than loan listings in subperiod 1, with this difference decreasing in subsequent subperiods. Relatively minor differences exist in the distributions of loan purposes for funded loans and loan listings.

4. Empirical Results

4.1. Shrinkage of the Interest Rate Distribution

In this section and the next, we evaluate the joint evolution of Prosper’s lending processes and the extent of the incorporation of soft information into interest rates. Following Rajan et al. (2015, Table 4), in this section we test our expectation that the distribution of interest rates on funded loans shrinks as Prosper eliminates peer lenders’ incorporation of soft information in setting interest rates in subperiod 2 under the pre-set pricing regime. We expect this distribution to continue to shrink, albeit to a lesser extent, in subsequent subperiods, as peer lenders can still use soft information in their loan funding decisions. We further expect this shrinkage to be larger for credit riskier loans, for which soft information is more important.

Figure 5 depicts the evolution in the distribution of interest rates over time. The figure presents box plots of the interest rates in each of the four subperiods for loans with the same credit rating (Panel A) or within the same credit score range (Panel B). As discussed in footnote 12, Prosper changed the primary credit scores it uses from Experian ScoreX PLUS in subperiods 1 to 3 to TransUnion FICO in subperiod 4. To ensure comparability, we discuss changes in interest rates for the credit score buckets only from subperiods 1 to 3, but we present the results in subperiod 4 using TransUnion FICOs for completeness. Not surprisingly, in each subperiod the median interest rate falls as credit ratings improve from the most risky (HR) to the least risky category (AA) and as credit scores increase. More interestingly, the interquartile range (IQR) decreases considerably from subperiod 1 to subperiod 4. This shrinkage in the distribution of interest rates is more pronounced for loans with middling or low credit ratings or credit scores than for loans with high ratings or scores.

Table 3 reports the mean and standard deviation of interest rates of funded loans in each subperiod by Prosper's proprietary credit rating categories or by credit score buckets.[17] Although these credit ratings and credit score buckets are fairly highly correlated, Prosper's proprietary credit ratings capture borrower credit risk more fully than do credit scores (Jagtiani and Lemieux 2017). Consistent with the box plots in Figure 5, the average interest rate decreases from subperiod 1 to subperiod 4 for all but the A credit rating. This rate decreases from subperiod 1 to subperiod 3 for the eight lowest credit score buckets, although it increases for the three highest

[17] In addition to unadjusted interest rates, in untabulated analysis we examine the distribution and predictive power of spreads over the US Treasury rates for the same maturity obtained from St. Louis Fed (https://fred.stlouisfed.org/series/DGS5 or https://fred.stlouisfed.org/series/DGS3), finding almost identical results. These and other untabulated results are available from the authors upon request.

buckets. As expected, the standard deviation of interest rates falls from subperiod 1 to subperiod 4 for all credit ratings, and from subperiod 1 to subperiod 3 for all credit score buckets. Also as expected, these decreases generally are larger for lower credit ratings and lower credit score buckets. For example, for AA-rated loans, the standard deviation of interest rates is 0.018 in subperiod 1 and declines by about 56% to 0.008 in subperiod 4. In contrast, for HR-rated loans, this standard deviation is 0.045 in subperiod 1 declines by about 84% to 0.007 in subperiod 4. For loans in the 778+ credit score bucket, this standard deviation of interest rates is 0.052 in subperiod 1 and declines by about 8% to 0.048 in subperiod 3. In contrast, for loans in the 660-619 credit score bucket, this standard deviation is 0.052 in subperiod 1 and declines by about 67% to 0.017 in subperiod 3.

We rule out various factors other than interest rates incorporating less soft information that could explain the shrinkage of the interest rate distribution over time. First, Prosper's proprietary credit ratings or credit bureaus' credit scores might capture borrower credit risk more fully over time. Undercutting this possibility, in untabulated analysis we estimate annual OLS regressions of credit ratings or credit scores on the borrower characteristics from *Home* to *Emp_length* reported in Table 2, and find the R^2s are stable over time.

Second, the increasing supply of capital in the peer-to-peer lending market might be attributable to peer lenders less rigorously screening the hard information in loan applications. Consistent with this possibility, Panel A of Table 1 (*FC_per_Request*) reports that the average funding rate for loan requests increases monotonically and substantially over time, from 28.8% in subperiod 1 under the auction regime to 95.5% in subperiod 4 under the pre-set pricing regime. Moreover, the funding rate rises more for lower-quality loans; for HR-rated loans, the funding rate rises by about eight times from 11.2% to 93.8%, whereas for AA-rated loans the funding rate only rises by about a half from 57.9% to 90.3%.[18] However, undercutting this possibility we also find that these results hold if we hold Prosper's credit screening standards fixed over time. To do this, we estimate a logistic regression of a loan origination indicator on the observable loan terms and borrower characteristics reported in Table 1 (from *List_Amount* to *Prior_Prosper_Loans*) for all loan requests in subperiod 1. We use the estimated coefficients to predict loan requests in subperiods 2 to 4 that would have been originated in subperiod 1. The standard deviation of interest rates also shrinks for these loan requests over time.

Third, and most plausibly, the shrinkage could be due to interest rates depending more on Prosper's credit ratings, rather than on hard information per se, over time. To investigate this possibility, Table 4 reports the estimation of annual OLS regressions of interest rates on indicators for either Prosper's seven credit ratings or the 11 credit score buckets, both with and without the standard financial variables reported in Panel A of Table 1 (from *List_Amount* to *Prior_Prosper_Loans*). Table 4, Panel A reports that the R^2s in regressions that include only Prosper's credit ratings as explanatory variables increase monotonically over time, from 0.89 in subperiod 1 to 0.96 in subperiod 4. Panel C reports that these R^2s rise only slightly when borrower characteristics and loan terms are added to the model. In contrast, Panel B reports that the R^2s in the regressions using only credit score buckets decrease non-monotonically over time, from 0.50 in subperiod 1 to 0.28, 0.39, and 0.37 in subperiods from 2 to 4, respectively. Panel D reports that these R^2s rise substantially when borrower characteristics and loan terms are added as explanatory variables, but they remain well below the R^2s reported in Panel A using only Prosper's credit ratings. These results are consistent with interest rates being driven more by

[18] Our inferences are unaffected by excluding loan requests that are withdrawn by borrowers or cancelled by Prosper within 1, 10, or 24 hours after they are posted on Prosper.com.

Prosper's proprietary credit ratings over time, not with interest rates incorporating more hard information per se.

4.2. Ability of Interest Rates to Predict loan default

The shrinkage of the interest rate distribution documented in the prior section suggests but does not imply that interest rates become less informationally efficient over time. To provide evidence on this issue, we evaluate changes over time in the ability of interest rates to predict loan default using logistic regressions. We measure this predictive power as the area under the receiver operating characteristic curve (AUC). In the default-prediction context, the receiver operating characteristic curve depicts the likelihood that a model correctly predicts default when it occurs (i.e., the true positive rate, or sensitivity) against the likelihood that the model incorrectly predicts default when it does not occur (i.e., the false positive rate, or one minus specificity). The AUC is the model's simple average true positive rate across all possible false positive rates. A higher AUC indicates the model has higher predictive power for default; random guessing yields an AUC of 0.50, while perfect prediction yields an AUC of 1.00. Iyer et al. (2016) state that AUC "is the most common metric used in the credit-scoring industry. As a rough rule of thumb, an AUC of 0.6 or greater is generally considered desirable in information scarce environments...Even a 0.01 improvement in AUC is considered a noteworthy gain in the credit scoring industry."

We expect the AUC to decrease as Prosper's shift from the auction regime to the pre-set pricing regime in subperiod 2 eliminates peer lenders' incorporation of soft information in setting interest rates, and to a lesser extent as Prosper reduces peer lenders' use of soft information in their loan funding decisions in subperiod 3 and particularly subperiod 4. We further expect this decrease to be larger for credit riskier loans, for which soft information is more important.

Table 5, Panel A reports logistic regressions of an indicator for loan default occurring at any time up to the data download date on the loan interest rate (*Loan_Rate*) for the overall sample in the four subperiods. We deem a loan to have defaulted if Prosper reports its status as "Default", "Chargeoff", or "Current" but more than 90 days past due (i.e., severely delinquent). The coefficient on *Loan_Rate* is positive and significant at the 1% level in each subperiod. Figure 6 depicts the ROC curve for each of the subperiods; the curve for subperiod 1 is above the curve in the other subperiods for the vast majority of false positive rates. As expected, the AUC is higher under the auction regime in subperiod 1 (0.669) than under the pre-set pricing regime in subperiods from 2 to 4 (0.639, 0.628, and 0.637, respectively). Non-parametric Chi-square tests indicate that the AUC in subperiod 1 is significantly higher than the AUC in each subsequent subperiod at the 1% level.[19, 20] These AUCs indicate that the interest rates set by Prosper under the pre-set pricing regime in subperiods from 2 to 4 only have 76% to 82% of the predictive power achieved by peer lenders under the auction regime.[21, 22]

Increased borrower risk over time is a possible alternative explanation for the declining predictive power of interest rates for default. In particular, Prosper may have loosened its credit standards to increase its growth, and it typically is more difficult to price credit riskier loans.

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[19] DeLong et al. (1988) develop this Chi-square test of the difference between the AUCs of two independent samples. We use the Stata command "roccomp" to conduct this test.

[20] Descriptive statistics reported in Table 2, Panel A indicate that the higher AUC in subperiod 1 is not attributable to the higher average interest rate in that subperiod than in subsequent subperiods driving borrowers into default. In fact, the frequency of default is lower in subperiod 1 than in subsequent subperiods.

[21] To make these calculations, we subtract 0.5 (i.e., the AUC for random prediction) from the AUCs for the subperiods, similar as Iyer et al. (2016). For example, we compute the proportion of the AUC in subperiod 2 relative to the AUC in subperiod 1 as (0.6390-0.5)/(0.6689-0.5)*100%=82.3%.

[22] At our data download date, 4,589 (5.65%) of the sample loans, largely from subperiods 3 and 4, remain outstanding. To ensure comparability across the subperiods, we exclude loans that remain outstanding at this date and repeat the analyses described in this paragraph, which yield the same inferences.

Undercutting this possibility, Table 2, Panel B reports that over time the median credit score of Prosper's borrowers increases, and the entire distribution of credit scores shifts slightly but noticeably to the right.

We conduct three analyses to ensure that the results for the overall sample are attributable to the reduced incorporation of soft information into interest rates, not to increased borrower risk. First, Table 5, Panels B and C report the predictive power of interest rates for default in each subperiod for the subsamples with poor credit ratings (C, D, E, and HR) and with good credit ratings (AA, A, and B), respectively; Iyer et al. (2016, Table 3 and Figures 4 and 5) split their sample at the same credit rating threshold. The interest rate is a significant predictor of defaults for both subsamples in each subperiod at the 1% level. Consistent with the performance of lower credit quality loans being more difficult to predict, Chi-square statistics reported in Panel C indicate that the AUCs are significantly smaller for the subsample with poor credit ratings than for the subsample with good ratings. Consistent with soft information being more important for lower credit quality loans, the predictive power of interest rates deteriorates significantly from subperiod 1 to subsequent subperiods for the subsample of loans with poor ratings, but not for the subsample of loans with good ratings.[23] For the subsample of loans with poor ratings, the AUCs indicate that the interest rates set by Prosper in subperiods 2-4 achieve only 45% to 76% of the predictive power of interest rates determined by peer lenders under the auction regime in subperiod 1.

Second, to control for changes in credit screening standards and/or borrower risk over time, we identify loans in subperiods 2-4 that would have been originated under the screening

[23] In untabulated analysis, we compare AUCs across periods for loans with the same credit rating. We observe a deterioration over time in the predictive power of interest rates for default for loans with credit ratings of C and below, but not for those with ratings of B and above.

standards of subperiod 1. We estimate subperiod 1 screening standards using a logistic regression of an indicator for origination of all loan listings in subperiod 1 on the observable loan terms and applicant characteristics from *List_Amount* to *Prior_Prosper_Loans* reported in Panel A of Table 1. We then compare the AUC for loans in subperiod 1 to the AUCs for the loans in subsequent subperiods that likely would have been originated in subperiod 1. We continue to find a significant decrease in AUCs over time.

Third, the credit quality of Prosper's borrowers might deteriorate unobservably from subperiod 1 to subperiod 4. For example, borrowers early adopting Prosper's peer-to-peer lending platform likely are technology savvy. As Prosper gains market share and reputation over time, it likely attracts people with more diverse backgrounds. While it is impossible to control directly for such unobservable borrower characteristics, in untabulated analysis we address this concern by splitting subperiod 1 into two parts. If differences between earlier and later adopters explain our results, we should see deterioration in the predictive power of interest rates for default from the early to late parts of subperiod 1, i.e., even before the switch from the auction regime to the pre-set pricing regime. However, we find no significant change in the predictive power of interest rates from the early to late parts of subperiod 1. These three analyses indicate that changes in borrower risk do not explain the deterioration in the predictive power of interest rates for default over time.

Increasing economic uncertainty over time is another possible alternative explanation for the lower predictive power of interest rates for default in the pre-set pricing regime. It is more difficult to set interest rates to reflect borrowers' credit risk at times of higher economic uncertainty. Undercutting this possibility, the U.S. economy became increasingly stable over our

August 2009 to February 2014 sample period as the financial crisis receded.[24] As discussed in footnote 17, we obtain almost identical results if we use interest rate spread (the loan interest rate minus the US Treasury rate for the same maturity) instead of the loan interest rate to predict loan default. However, it is possible that economic uncertainties specific to peer-to-peer lending rise over the sample period.

We address this concern by examining the predictive power of interest rates for loans originated by Lending Club (LC), Prosper's main competitor. As the two largest peer-to-peer lenders, Prosper and LC have experienced similar explosive growth over time and have similar clienteles. Like Prosper, LC changed its lending process as it grew, for example, adding a whole loan channel on September 28, 2012[25] and removing loan descriptions in April 2014, two months after our sample period. However, unlike Prosper, LC has set interest rates based on proprietary credit ratings throughout its life, rendering it ideal for a placebo test.[26, 27] If the deterioration of the predictive power of Prosper's loan interest rates for loan default is attributable to increased economic uncertainty, we should observe similar deterioration for LC's loans.

Similar to the analysis reported in Table 3 for Prosper, Table 6, Panel A reports the distribution of LC's loan interest rates during each of the four subperiods for each of its

[24] In untabulated analysis, we find that our inferences are unaffected by excluding the sample period immediately after the financial crisis (e.g., starting the sample in January 2010).

[25] https://www.lendacademy.com/lending-club-whole-loan-program-one-year-later/

[26] Given the differences between the two platforms, especially during the auction regime in subperiod 1 when LC pre-set interest rates, it is possible that the two lending platforms may attract different borrowers. In untabulated analysis, we compare the average credit scores, monthly income, and debt-to-income ratio for applicants at Prosper and LC. We find that Prosper's applicants have worse credit profiles than LC's applicants before the regime switch in December 2010, and that subsequently this difference gradually diminishes. Since it is more difficult to price riskier loans, this change in applicant composition biases against our finding that Prosper's peer lenders achieved better predictive power in the auction regime than in the pre-set pricing regime.

[27] In the bulk download file (https://www.lendingclub.com/info/download-data.action), LC only reports the month in which loans are originated. This file does not provide the dates when loan requests are submitted and originated. LC also provides very limited information on unfunded loan applications (including loan applications that never listed on its platform or listed but not funded). We scraped LC's prospectus listing supplements and sales supplements (Form 424B3) to obtain the dates of loan applications and originations, as well as standard credit variables such as credit score buckets and debt-to-income ratio.

proprietary credit ratings (A, B, C, D, E, F, and G) or TransUnion FICO credit score buckets. In striking contrast to the statistics for Prosper reported in Table 3, Panel A of Table 6 reports that, for each credit rating and credit score bucket, the average interest rate on LC loans increases over time, and the standard deviation of interest rates remains stable or slightly increases from subperiod 1 to subperiod 4.

Table 6, Panel B reports the AUCs from the logistic regressions of the default indicator on interest rates for the subsamples of LC loans with good credit ratings (A, B, and C) and poor ratings (D, E, F, and G), respectively. We find no significant changes in the predictive power of interest rates for either subsample of loans over time. The results of this placebo test suggest that the deterioration in the predictive power of interest rates for default on Prosper loans over time is attributable to changes in its lending processes, not to increased economic uncertainty.

4.3. Partitioning on the Extent of Soft Information

The evidence discussed above suggests that the loss of soft information resulting from the switch from the auction regime to the pre-set pricing regime in subperiod 2 reduces the predictive power of interest rates for default. In this section, we examine one source of soft information available on Prosper's lending platform: in subperiods 1-3, but not in subperiod 4, loan applicants have the option to provide descriptions of their personal circumstances and intended loan purposes. These loan descriptions contain decidedly soft information. Prosper does not verify the accuracy of loan descriptions. In fact, the information contained in these descriptions generally is not verifiable. Appendix B reproduces a representative loan description. We chose loan descriptions as the source of soft information to analyze in part because loan applicants provide these descriptions with reasonable frequency in subperiods 1-3, and in part because in these subperiods there is quantifiable cross-sectional variation in the soft information provided.

Prior research shows that loan descriptions affect peer lenders' funding decisions. Using Prosper's loan requests between February 2007 and October 2008, Michels (2012) develops a nine-element disclosure index that quantifies the level of detail in loan descriptions. He finds that, after controlling for standard financial variables, an additional element in loan descriptions is associated with a 1.27 percentage point reduction in interest rates and a 3.28% increase in the likelihood of loan origination. He finds that the impact on interest rates is larger for lower-rated loans, consistent with soft information being more useful in screening risky borrowers. Lastly, he finds that the disclosure index is significantly negatively associated with loan defaults, suggesting that lenders' reliance on loan descriptions is justified. Not all of the details in loan descriptions have positive effects, however. Netzer et al. (2016) find that the descriptions for loans that subsequently default are more likely to include words related to family, God, short-term focus, the borrower's financial and general hardship, and pleading for help from lenders.

We employ two measures of the amount of soft information in loan descriptions. The first and simpler measure is the number of words in (hereafter "length of") the descriptions. We assume that longer descriptions contain more soft information. Each year, we split the sample loans for which the loan applicants provide loan descriptions into groups with above- and below-median length descriptions. We examine the predictive power of interest rates for default of loans originated in each subperiod with above- versus below-median length loan descriptions. We also examine the changes in these predictive powers from subperiod 1 to subsequent subperiods.

Table 7, Panel A reports the results. The top (bottom) half of the panel examines loans with poor (good) credit ratings. The leftmost (rightmost) three columns examine loans with above-median (below-median) length loan descriptions. We find that, for loans originated in subperiod 1 under the auction regime, above-median length loan descriptions are associated with higher predictive power of interest rates for default for loans with poor credit ratings, but not for loans with good credit ratings. For loans with poor credit ratings, the AUC is 0.61 and 0.58 for loans with above-median and below-median length descriptions, respectively, with the difference in these AUCs being significant at the 5% level. In subsequent subperiods under the pre-set pricing regime, we find no significant difference in this predictive power for loans with above- versus below-median length loan descriptions.

For loans with poor credit ratings and above-median length loan descriptions, we further find that the predictive power of interest rates is significantly higher in subperiod 1 under the auction regime than in subsequent subperiods under the pre-set pricing regime. We find no such time-series variation in the AUCs for loans with poor credit ratings and below-median length descriptions, or for loans with good credit ratings regardless of the length of loan descriptions.

The second and more involved measure of the amount of soft information is the number of topics in loan descriptions (hereafter, the "disclosure index"). We compiled the following list of topics from Michels (2012) and Netzer et al. (2016): loan purpose, family life or family members, prior loans with Prosper, credit details, job prospects, monthly income, monthly expenses, explanation for negative information in the credit profile, and pleading for help from lenders.

We use Python's supervised machine learning packages (skmultilearn) to automate the identification of these topics.[28] We first randomly selected 400 loan descriptions as training data

[28] We use machine learning rather than a keyword-based classification method because the latter is less flexible and could yield higher type I and type II errors depending on the comprehensiveness of the keyword lists. For example, the description for a home improvement loan might not include the words "home improvement", "repair", "replace", "upgrade" or even "home", but might instead say "fix my mom's house it is in need of a new roof" or "update my kitchen". By using all the words in the LIWC category "home"—which includes, for example, "apartment", "backyard", "kitchen", and "carpet"—and taking into account patterns in other word categories, machine learning can more accurately classify topics. Comparing machine learning to the keywords-based method developed by

and manually read and classified each description as containing or not containing the topics mentioned above.[29] If we determine that a loan description mentions one of these topics, we code that topic as one for that loan request, and zero otherwise. We provide Python with the simplified loan descriptions described below and our classifications for the training data, and ask it to determine how we mapped the descriptions to classifications.

We simplify loan descriptions as follows. First, we exclude stop words (e.g., "the" and "and") and convert words to their stems (e.g., "consolidate" and "consolidation" share a stem). After this step, the training data still contain 1,470 unique stems, over three times the size of our training sample, allowing perfect classifications of the loan descriptions in that sample, but poorly classifying out-of-sample loan descriptions. Following Netzer et al. (2016), we use the 2015 Linguistic Inquiry and Word Count (LIWC) dictionary to group word stems with similar meaning or purpose into a single category. We further exclude 16 categories that appear in less than 0.1% of loan descriptions (often combinations of filler and informal words).

We use multi-label classification because loan descriptions may contain multiple topics. We use the linear support vector machine learning method, because it is most suitable for classifications involving a large number of sparsely populated features, such as the linguistic features of texts (Joachims 1998). Once Python "learns" how we classify the loan descriptions in the training sample, it applies the method to the remaining loan descriptions.[30] We construct the

experts to classify the topics of news articles, Apte et al. (1994) show that machine learning is as accurate as but requires less time and effort to develop than the keyword-based method. The primary disadvantage of machine learning is the classification process is a black box.

[29] As different loan purposes exhibit different linguistic features, to improve the accuracy of machine learning, we separately classified the loan purposes of debt consolidation, business loan, auto loan, tax loan, home improvement and reallocation, school-related loan, and medical loan. The loan purpose topic takes a value of one rather than the total number of identified loan purposes for a loan description that mentions one or more of these loan purposes.

[30] To evaluate the performance of our machine learning method, we randomly select a test sample of 100 descriptions out of the training sample and use the remaining 300 descriptions to train Python. We find that Python's classifications are correct for 90% of the topics present in the test sample, with its accuracy ranging from 83% to 97% across topics.

disclosure index based on the number of topics identified from each loan description. Similar to the analyses of loan description length, we partition descriptions each year into above- and below-median disclosure index groups for each credit rating. We compare the predictive power of interest rates for default for the above- versus below-median disclosure index groups in each subperiod and for each group across the subperiods.

Table 7, Panel B reports the results of this analysis. These results generally are consistent with those for the loan description length reported in Table 7, Panel A. For loans originated in subperiod 1 under the auction regime, above-median disclosure index loan descriptions are associated with higher predictive power of interest rates for default on loans with poor credit ratings, but not on loans with good credit ratings. For loans with poor credit ratings, the AUC is 0.61 and 0.58 for loans with above-median and below-median disclosure index descriptions, respectively, with the difference in these AUCs being significant at the 5% level. In subperiod 2 under the pre-set pricing regime, we find a considerably smaller and only weakly (10% level) significant difference in this predictive power for these loans with above- versus below-median disclosure index descriptions. The difference is insignificant in subperiod 3. For loans with poor credit ratings and above-median disclosure index loan descriptions, we also find that the predictive power of interest rates is significantly higher in subperiod 1 under the auction regime than in subsequent subperiods under the pre-set pricing regime. We find no such time-series variation in the AUCs for loans with poor credit ratings and below-median disclosure index descriptions, or for loans with good credit ratings regardless of the disclosure index.

Collectively, the results reported in Table 7 suggest that the deterioration of the predictive power of interest rates for default over time is attributable to the switch from the auction regime to the pre-set pricing regime reducing the incorporation of soft information in interest rates. In

Appendix C, we confirm that our soft information measures have consistent implications for lenders' funding commitment as a percentage of the borrower's requested loan amount (*FC_per_Request*). Similar to Michels (2012), the appendix provides evidence that both soft information measures are significantly positively associated with *FC_per_Request*, and that this association is stronger for loan listings with poor credit ratings than with good credit ratings in subperiod 1 but not in subsequent subperiods.

4.4. Benefits of Transaction Processing Efficiency and Diversification

Although we provide evidence that the interest rates determined by peer lenders under the auction regime are more predictive of default than those set by Prosper under the pre-set pricing regime, the regime change need not adversely affect investors, because the increased volume and speed of Prosper's loan origination under the pre-set pricing regime could facilitate lenders' diversification of their loan portfolios. As reported in Table 2, Prosper's average number of loan originations per day increases from 22 in subperiod 1 to 40 in subperiod 2, 87 in subperiod 3, and 156 in subperiod 4. The funding time drops from 149 hours in subperiod 1 to 88 in subperiod 2. It then further falls to 16 and 5 in subperiod 3 and 4, mainly driven by institutional investors investing in the whole-loan channel.

To quantify the impact of Prosper's three policy changes on its transaction processing efficiency, we examine the daily dollar amounts of loan applications and funded loans, as well as the median delay from loan application to loan origination around these changes.[31] To control for changes in macroeconomic and other economic variables affecting peer-to-peer lenders, we estimate difference-in-differences models that compare the difference for Prosper versus LC in

[31] Ideally, we would like to compare the funding speed measured by the time that elapses during the funding process. Prosper provides this measure (*Funding_Time*), which declined over time as reported in Table 2. However, LC does not provide the exact times when it posts and funds loan requests. To compare funding speed between Prosper and LC, we count the days from loan application to origination, a somewhat crude measure of the desired construct.

the differences from three months before to three months after each policy change. We emphasize that these results should be interpreted with some caution, as the treatment and control groups each reflect the loan applications and originations for only one lender. Hence, idiosyncratic variation for either lender that coincides with but is unrelated to the policy change under examination could affect the estimations. Moreover, the peer-to-peer lending market is a near duopoly, with LC and Prosper being the industry leaders, and a successful strategic decision by one of these lenders typically is followed by a mimicking decision by the other.[32]

Table 8 reports the results of the difference-in-differences estimations, with Panel A examining the switch from the auction to pre-set pricing regimes, Panel B the whole loan channel launch, and Panel C the elimination of loan descriptions. The dependent variables in the various models are indicated in the column headers. For all models, the variable of interest is the interaction term *Prosper*Post*, which captures the change in transaction processing efficiency in response to the policy change under examination. Panel A shows the switch to the pre-set pricing regime is associated with a 62.6% decrease in loan application volume, 13.9% increase in loan origination volume, and 31.5% reduction in the delay from loan application to origination (or 31.5% improvement in loan origination speed). As discussed in footnote 1, the reduction in loan application volume likely is driven in part by some applicants being discouraged by high pre-set interest rates and withdrawing their loan requests before they are posted on Prosper.com. Panel B shows that the launch of whole loan channel is associated with a 30.6% increase in loan application volume, 42.4% increase in loan origination volume, and 17.3% reduction in loan origination delay. Panel C shows that the elimination of loan descriptions is associated with a 47.2% increase in loan application volume, 33.2% increase in loan origination volume, and 26.2%

[32] For example, LC has pre-set interest rates since its inception, followed by Prosper in December 2010. LC launched the whole loan channel in September 2012, followed by Prosper in April 2013. Prosper disallowed loan descriptions in September 2013, followed by LC five months later.

increase in the loan origination delay. As discussed in Section 2, the main purpose of eliminating loan descriptions is to streamline the *application* process, hence we have no expectations about how this elimination affects loan funding conditional on the posting of applications. Panel C shows that delay decreases around the elimination of loan descriptions for Prosper, however, it decreases more for LC, yielding a positive coefficient on *Prosper*Post*. Collectively, the results show a significant improvement in the transaction processing efficiency associated with Prosper's three policy changes.

We expect that improved transaction processing efficiency benefit lenders by enhancing their ability to diversify. To test this expectation, we construct portfolios by randomly selecting 5 or 10 or 20 loans with the same credit rating and subperiod and test the ability of the loan-amount-weighted portfolio interest rates to predict two measures of portfolio performance. First, we use a binary indicator for whether the portfolio contains any defaulted loans as the dependent variable in logistic regressions, and we compare AUCs across different samples. In our sample, the probability of default on a single loan is 19.6%, while the probability of default on a 5- (10-) [20-] loan portfolio is 65% (85%) [95%]. A limitation of this binary indicator for default is that larger portfolios are more likely to contain defaulted loans. To better capture variation in portfolio performance, we also measure portfolio performance using the proportion of unpaid principal as of our November 12, 2017 data download date.[33] The drawback of this measure is that we cannot compare the predictive power across samples using AUC, and so we instead use R^2.

Table 9 reports the results of this analysis. Panel A (B) reports the results using the indicator for default (proportion of unpaid principal) in the portfolio. Using the default indicator,

[33] We exclude 4,589 (5.65%) active loans on the data download date from the analyses.

the predictive power of interest rates increases with portfolio size. More importantly, we observe no significant deterioration in the ability of interest rates to predict portfolio defaults over time for any of the three portfolio sizes. The results using the proportion of unpaid principal are consistent with those using the default indicator. For a single loan, the regressions of unpaid principal on interest rates yield a slightly higher R^2 in subperiod 1 than other periods, although the R^2s are rather low, ranging from 0.048 in subperiod 1 to 0.031 in subperiod 3. The R^2s increase substantially with portfolio size. More importantly, we observe no significant deterioration in the ability of interest rates to predict the proportion of unpaid principal over time for any portfolio size.

Overall, the evidence discussed in this section indicates that the predictive power of interest rates for loan performance on modestly sized portfolios does not deteriorate over time. This evidence obtains despite the fact that interest rates set by Prosper under the pre-set pricing regime reflect less soft information about borrower creditworthiness than do the interest rates determined by peer lenders under the auction regime. The evidence highlights the benefits of diversification and perhaps justifies the reduced screening by peer lenders evidenced by the increased funding rate over time discussed above.

4.5. Use of Soft Information by Individual versus Institutional Investors

As discussed in Section 2, at the beginning of subperiod 3 Prosper launched a whole loan program that primarily caters to institutional investors. In this section, we test whether individual investors are more likely to incorporate soft information than are institutional investors. Extant studies report disparate findings regarding whether institutional investors outperform retail investors in the different online lending market settings. Lin et al. (2017) find that institutional lenders do not necessarily outperform peer lenders using Prosper loans posted from January 19, 2008 to September 19, 2008, while Vallee and Zeng (2018) find that sophisticated investors systematically outperform using a subsample of Prosper and LC loans funded between January 2014 and February 2017. We attempt to reconcile this divergence from the perspective of soft information processing, as the availability and prevalence of soft information substantially differ across the two subperiods.

Specifically, we compare the predictive power of interest rates (as measured by AUC) of the loans originated via the fractional loan versus whole loan channels. We further distinguish borrowers with loan descriptions that contain more versus less soft information to study the role of soft information. Because Prosper launched the whole loan channel in subperiod 3 and eliminated loan descriptions in subperiod 4, most of this analysis is limited to subperiod 3.

Table 10 reports the results of this analysis. Panel A distinguishes fractional and whole loans for the overall sample and for the subsamples of loans with poor or good credit ratings. As before, we expect soft information to be most important for loans with poor credit ratings. Consistent with this expectation, for loans with poor credit ratings we find that the AUC is significantly higher for fractional loans than for whole loans. We find smaller and insignificant differences in AUCs for loans with good credit ratings and for the overall sample, consistent with Lin et al.'s (2017) findings that institutional investors do not achieve significantly better performance than retail investors in the peer to peer lending market.

Panel B distinguishes fractional loans with poor versus good credit ratings based on the soft information contained in loan descriptions as measured by their length. We further expect longer descriptions to be most important for fractional loans with poor credit ratings. Consistent with this expectation, for loans with poor credit ratings we find that the AUC is weakly significantly (10% level) larger for fractional loans with above-median length descriptions than for whole loans. In contrast, the AUC for fractional loans with below-median length descriptions is not significantly different than the AUC for whole loans. For loans with good credit ratings, we find insignificant differences in AUC for fractional loans with either length descriptions than for whole loans. Panel C distinguishes loans with poor credit ratings and loans with good credit ratings based on the soft information contained in loan descriptions as measured by the disclosure index. The results in this panel yield the same inferences as in Panel B.

In Panel D, we explore the effect of the elimination of loan descriptions in subperiod 4. We expect that retail (peer) investors are more likely to incorporate this soft information than are institutional investors. We expect that the predictive power of interest rates on fractional loans equals that of interest rates on whole loans after loan descriptions are removed. As mentioned above, Prosper launched the whole loan channel for passive institutional investors early in subperiod 4. Hence, we compare fractional loans to whole loans issued in the active and passive channels with the same credit ratings. Consistent with this expectation, Panel D reports that the AUCs for three types of loans are insignificantly different in subperiod 4. This finding suggests that the higher predictive power of interest rates of fractional loans in subperiod 3 is attributable to the soft information in loan descriptions. Lastly, we find that the AUC of fractional loans with poor (good) credit ratings decreases from 0.572 (0.604) in subperiod 3 to 0.543 (0.580) in subperiod 4, although these differences are not statistically significant. The AUCs of whole loans funded by active institutional investors slightly increase from subperiod 3 to subperiod 4, although the differences are again insignificant.

Collectively, the findings in this section are consistent with individual investors processing soft information more fully than do institutional investors. Our results identify soft information processing as one source of individual investors' advantage over sophisticated institutional investors. These results help explain why Lin et al. (2017) find that sophisticated investors do not outperform retail investors in the online lending market.

5. Conclusion

In this study, we provide quantitative evidence of the informational costs and transaction processing efficiency benefits of three major changes in its lending processes that Prosper, the second largest online peer-to-peer lending platform in the U.S., has made to effect or respond to the evolution of the peer-to-peer lending industry. Prosper has (1) changed the way it sets the interest rates on loans from auctions among peer lenders to a proprietary credit-rating model in December 2010; (2) enabled institutional investors to fund whole rather than just fractional loans in April 2013; and (3) reduced the extent of soft information available to peer lenders in September 2013. Each of these changes has traded off the aggregation of soft information by peer lenders in favor of the speed and volume of transaction processing, a trade-off very similar to the extensively studied one made by large traditional banks in emphasizing hard rather than soft information.

On the cost side, we find that, after the December 2010 change, the distribution of loan interest rates shrinks and the ability of interest rates to predict loan default deteriorates, particularly for loans to low credit quality borrowers for whom soft information is more important for credit screening. Similarly, after the April 2013 change interest rates for low credit quality loans in the fractional loan market are more predictive of default than are interest rates in the whole loan market. On the benefit side, we find that, after each of these changes, the average time to fund and the average requested amount funded rise sharply, and the average interest rate falls appreciably for low credit quality borrowers. Moreover, the cost of the loss of soft information appears manageable, as peer lenders' ability to diversify increases and the interest rates of a modest-size portfolio of Prosper loans remain just as predictive of default. A placebo test using Lending Club, a peer-to-peer lender that did not change its lending processes during our sample period, indicates that the effects we document are attributable to the changes in Prosper's processes.

As discussed the introduction, our paper contributes to literatures in FinTech, banking, and other areas that: (1) examine the "wisdom of the crowd"; (2) show the importance of soft information in credit screening and monitoring in general and in peer-to-peer lending in particular; (3) provide evidence that FinTech has led to increased reliance by traditional banks on hard information in credit screening and monitoring and efficiency and growth in various loan markets; and (4) examine the efficiency of peer-to-peer lending. In addition, consistent with prior evidence in Navaretti et al. (2017), our finding that a supervised machine learning generated index of the amount of soft information in loan descriptions improves pricing efficiency suggests that peer-to-peer lending platforms can apply natural language recognition and interpretation techniques to loan descriptions and other textual forms of soft information to set interest rates and for other lending decisions.

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Figure 1. Major Changes in Prosper's Lending Processes

This chart depicts the timeline of the key changes in Prosper's lending processes from its registration with the SEC in July 2009 to the end of our sample period in February 2014. These changes demarcate the four subperiods that we examine empirically. In December 2010, Prosper changed the way it sets interest rates from reverse auctions among peer lenders to pre-set pricing based on a proprietary credit-rating model. In April 2013, Prosper enabled institutional investors to fund whole loans in addition to fractional loans. In September 2013, Prosper eliminated borrowers' ability to provide narrative disclosures of their life circumstances and intended loan purposes, thereby reducing the soft information available to peer lenders.

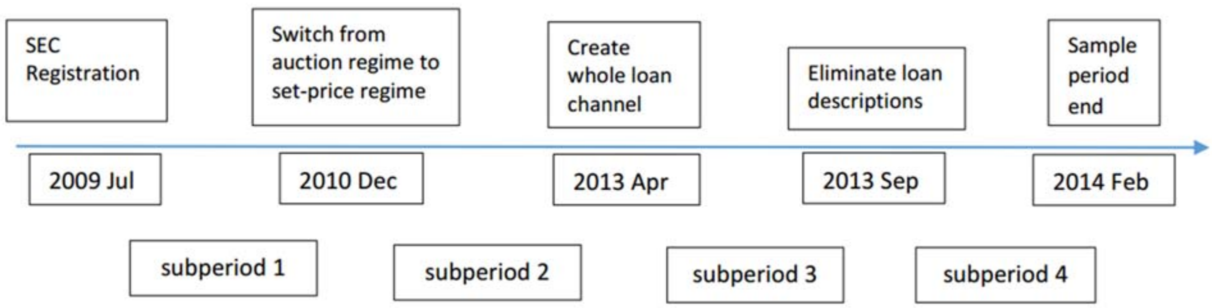


Figure 2. Lending Volume (Prosper)

The left (right) chart plots Prosper's volume of loan requests (loan originations) in each sample quarter. The left (right) axis represents the number (dollar amount) of loan requests or originations.

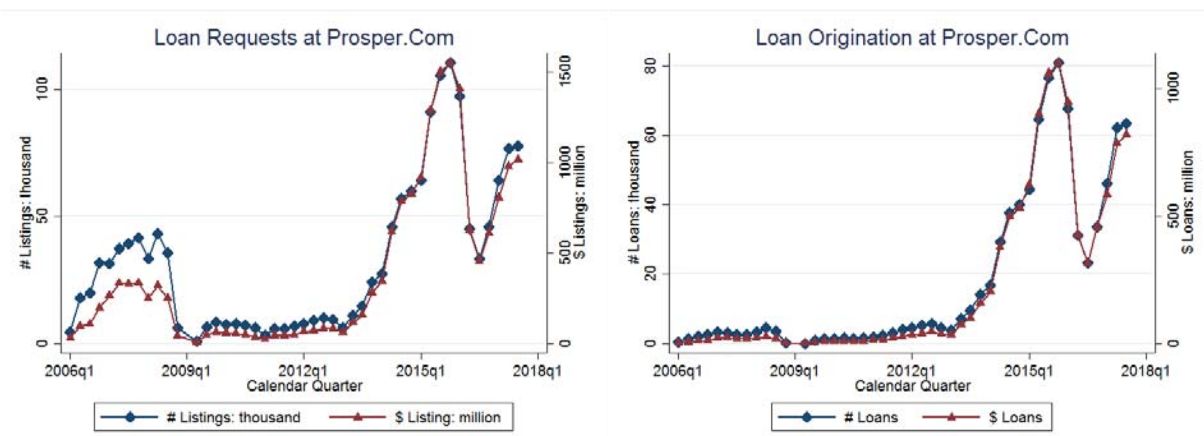


Figure 3. Funding Commitment (Prosper)

This figure plots the average funding rate—i.e., the funding commitment offered by lenders divided by the requested loan amount—across all loan listings on Prosper's lending platform in each sample quarter. Listings for which lenders offer funding may yield funded loans, expire, be withdrawn by borrowers, or be canceled by Prosper.

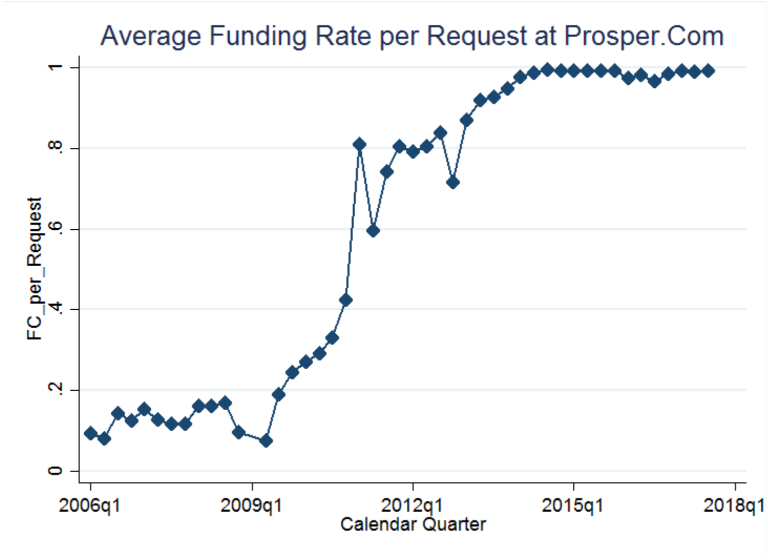


Figure 4. Funding Speed (Prosper)

This figure plots the average hours from the posting of a loan request on Prosper's lending platform to the end of the funding period in each quarter of Prosper's life. We differentiate requests posted in the fractional loan channel, the whole loan channel that caters to active institutional investors, or the whole loan channel that caters to passive institutional investors. We exclude 4,591 loans originated after the stated maximum funding time of 14 days.

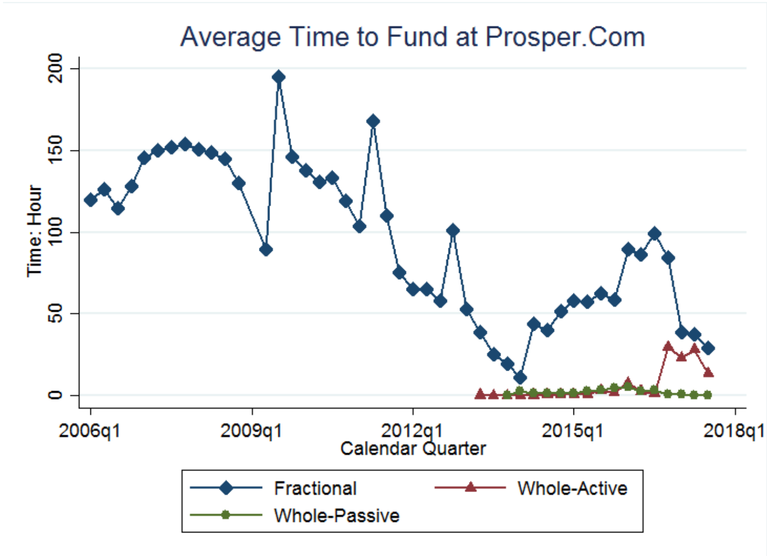
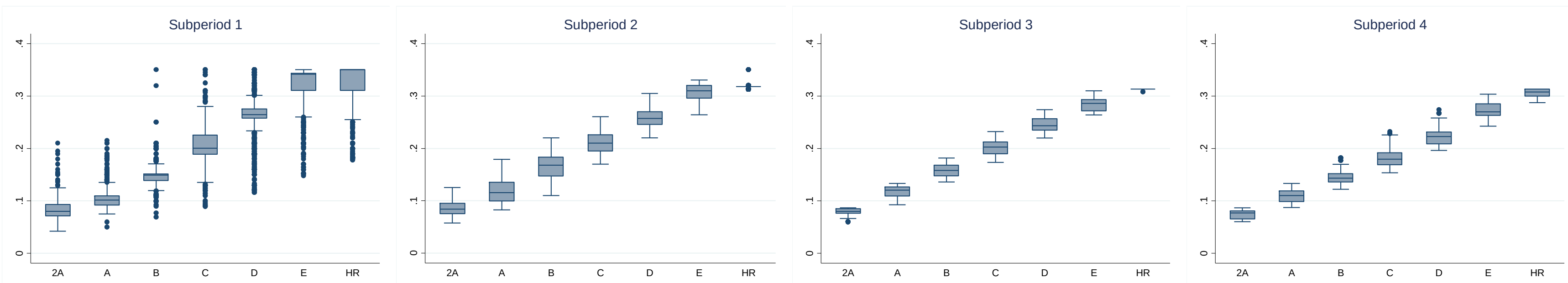


Figure 5. The Distributions of Interest Rates across Subperiods (Prosper)

These figures present box plots of the interest rates on Prosper loans in each of the four subperiods. These subperiods reflect Prosper's major changes in its lending processes during the sample period as discussed in Section 2 and summarized in Figure 1. The box plots depict the maximum, 75th percentile, median, 25th percentile, and minimum interest rates within the same Prosper rating (credit score bucket) in Panel A (B). If maximum (minimum) interest rate is above (blow) 1.5 interquartile range of the 75th (25th) percentile, they are plotted as individual points. Credit score buckets 2-11 represent the Experian ScoreX PLUS score ranges of [600-619], [620-639], [640-649], [650-664], [665-689], [690-701], [702-723], [724-747], [748-777], 778+, respectively. Prosper switched the primary credit scores it uses from Experian ScoreX PLUS to TransUnion FICO in subperiod 4, hence the box plots for subperiod 4 in Panel B are for TransUnion FICO score buckets.

Panel A: Partition by Prosper Credit Ratings



Panel B: Partition by Credit Score Buckets

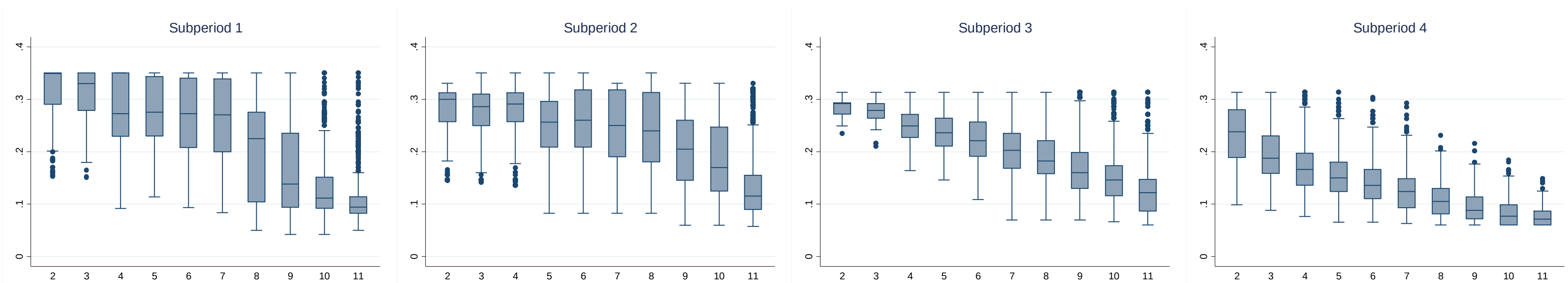


Figure 6. ROC Curves for the Prediction of Loan Defaults Based on Interest Rates (Prosper)

This figure plots the receiver operating characteristic (ROC) curve for the prediction of loan default based on interest rates on loans listed in each of the four subperiods. These subperiods reflect Prosper's major changes in its lending processes during the sample period as discussed in Section 2 and summarized in Figure 1. The area under each ROC curve (AUC) is reported in the legend.

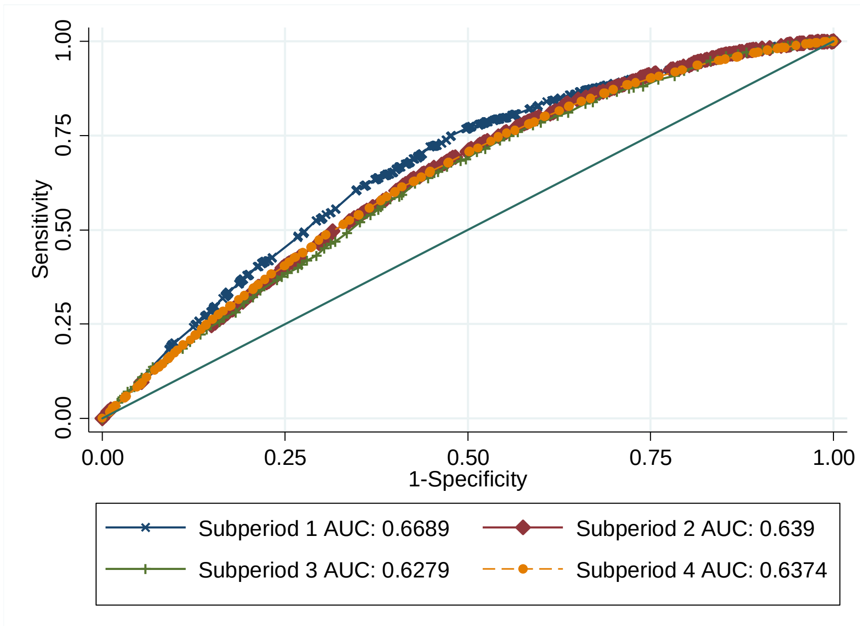
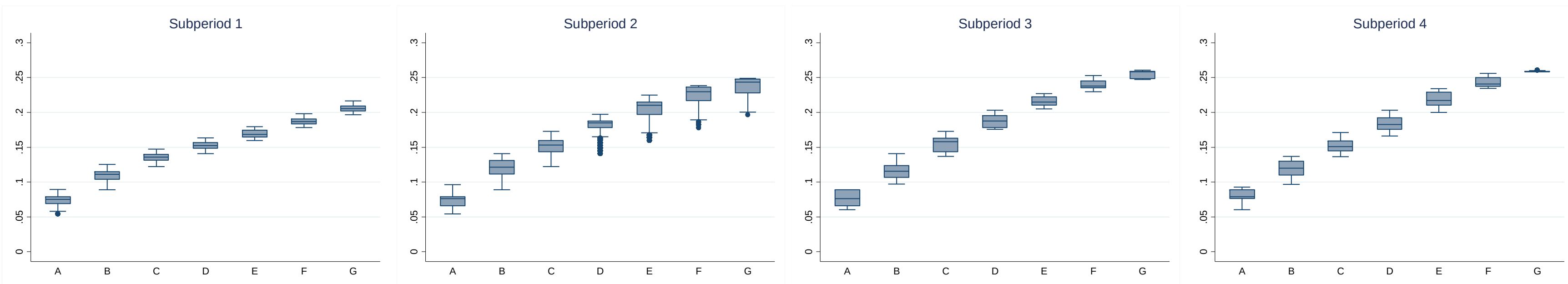


Figure 7. The Distributions of Interest Rates across Subperiods (Lending Club)

These figures present box plots of the interest rates on Lending Club (LC) loans in each of the four subperiods. These subperiods reflect Prosper's major changes in its lending processes during the sample period as discussed in Section 2 and summarized in Figure 1. The box plots depict the maximum, 75th percentile, median, 25th percentile, and minimum interest rates within each proprietary LC rating (credit score bucket) in Panel A (B). If the maximum (minimum) interest rate is above (blow) 1.5 interquartile range of the 75th (25th) percentile, they are plotted as individual points. Credit score buckets 1-7 represent FICO score ranges of [660, 679], [680-699], [700-719], [720-739], [740-759], [760-779], and 780+, respectively.

Panel A. Partition by LC Credit Ratings



Panel B. Partition by Credit Score Buckets

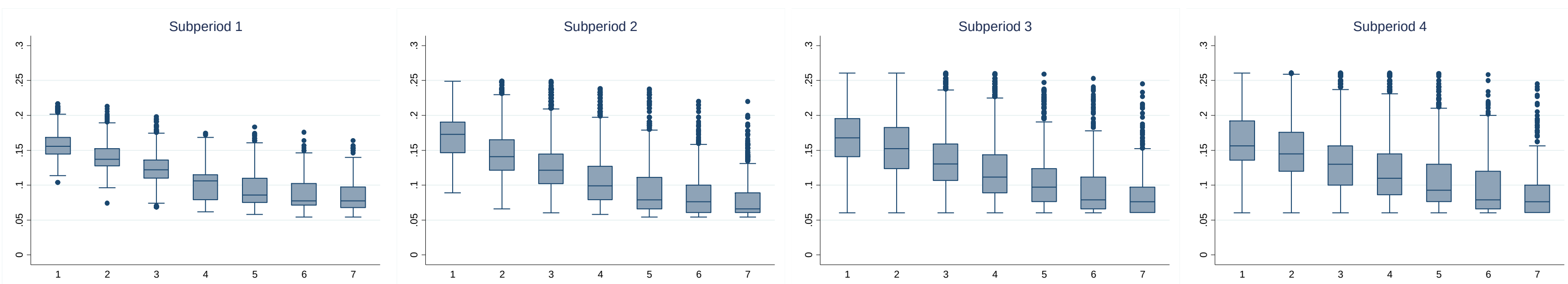


Table 1. Summary Statistics for Loan Listings

Panel A of the table reports the means and standard deviations of the loan terms and loan applicant characteristics for the loan requests posted on Prosper's lending platform in each the four subperiods described in Section 2 and summarized in Figure 1. These subperiods reflect Prosper's major changes in its lending processes during the sample period. Panel B reports the distributions of listing statuses, credit score buckets, and loan purposes for these loan listings. Appendix A contains the definitions of all variables.

Panel A: Loan terms and loan applicant characteristics

	subperiod 1 41,706 listings (83/day)		**subperiod 2 62,870 listings (75/day)**		**subperiod 3 19,266 listings (131/day)**		**subperiod 4 45,768 listings (260/day)**	
VARIABLE	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
List_Rate	0.246	0.094	0.226	0.075	0.188	0.061	0.166	0.056
List_Amount	7067	5627	8399	5710	10573	6642	11824	6917
Maturity5Y	0.002	0.047	0.28	0.449	0.457	0.498	0.333	0.471
Home	0.512	0.5	0.499	0.5	0.546	0.498	0.509	0.5
DTI	0.275	0.176	0.234	0.154	0.248	0.125	0.249	0.113
MissingDTI	0.215	0.411	0.129	0.336	0.06	0.237	0.053	0.223
Income	5280	11405	6367	37294	6407	7942	6904	13371
Bankcard_Utilization	0.544	0.348	0.493	0.322	0.558	0.287	0.591	0.281
Creditlines_7Years	26.087	14.62	25.694	13.694	28.699	12.705	28.202	12.838
Open_creditlines	8.449	5.025	8.269	4.853	10.155	4.779	10.448	4.943
current_delinquencies	0.438	1.235	0.41	1.225	0.345	1.163	0.204	0.826
delinquencies_7years	3.146	8.335	3.658	9.259	3.507	9.255	3.4	9.117
Inquiries_6months	1.533	2.117	1.182	1.662	0.824	1.293	0.931	1.246
public_records_10years	0.241	0.624	0.264	0.704	0.266	0.643	0.301	0.651
public_records_12months	0.013	0.126	0.013	0.131	0.009	0.232	0.004	0.068
Credit_History	186.8	93.7	210.5	100.1	228.8	97.8	223.5	99.3
Employed	0.799	0.401	0.846	0.361	0.899	0.302	0.872	0.334
Emp_Length	6.584	7.108	8.109	8.124	9.412	8.57	8.896	8.553
Prior_Prosper_Loans	0.289	0.567	0.294	0.673	0.307	0.728	0.126	0.506
Partial_Funding			0.756	0.430	0.798	0.402	0.966	0.182
Group_Affiliation	0.071	0.257	0.025	0.158	0.014	0.117	0.007	0.086
Des_Dummy	0.999	0.037	0.771	0.420	0.687	0.464		
Des_Length	138.13	81.28	73.167	54.69	55.732	54.63		
Des_Index	3.242	1.594	2.172	1.619	1.582	1.551		
FC_per_Request	0.288	0.417	0.777	0.376	0.925	0.257	0.955	0.204
1(Fractional)					0.531	0.500	0.333	0.432
1(Whole-Active)					0.469	0.499	0.389	0.488
1(Whole-Passive)							0.278	0.448

Panel B: Distributions of listing statuses, credit score buckets, and intended loan purposes

	# of obs in each subperiod				% of obs in each subperiod			
	1	2	3	4	1	2	3	4
Listing Status								
Cancelled	1,615	14,614	5,144	16,581	3.87	23.24	26.7	36.23
Completed	7,443	33,852	12,816	27,143	17.85	53.84	66.52	59.31
Expired	17,439	5,675	65	36	41.81	9.03	0.34	0.08
Withdrawn	15,209	8,729	1,241	2,008	36.47	13.88	6.44	4.39
ScoreX								
<600	0	0	0	555	0	0	0	1.21
600-619	956	781	159	1,102	2.29	1.24	0.83	2.41
620-639	1,286	1,341	306	3,013	3.08	2.13	1.59	6.58
640-649	4,091	1,957	560	2,291	9.81	3.11	2.91	5.01
650-664	5,752	5,165	1,135	3,820	13.79	8.22	5.89	8.35
665-689	7,280	11,823	3,198	6,718	17.46	18.81	16.6	14.68
690-701	3,025	5,988	1,625	3,459	7.25	9.52	8.43	7.56
702-723	5,344	9,690	3,220	6,602	12.81	15.41	16.71	14.42
724-747	4,798	9,350	3,237	6,562	11.5	14.87	16.8	14.34
748-777	4,412	8,229	3,157	6,228	10.58	13.09	16.39	13.61
778+	4,762	8,546	2,669	5,418	11.42	13.59	13.85	11.84
Intended Loan Purpose								
Debt Consolidation	19,577	28,517	13,291	35,395	46.94	45.36	68.99	77.34
Home Improvement	3,417	7,546	1,618	2,100	8.19	12	8.4	4.59
Business	6,219	6,604	850	1,505	14.91	10.5	4.41	3.29
Student use	1,630	0	0	0	3.91	0	0	0
Auto / Motorcycle / RV / Boat	2,186	2,556	278	513	5.24	4.07	1.44	1.12
Other	8,677	9,129	1,069	3,124	20.81	14.52	5.55	6.83
Baby & Adoption	0	231	55	107	0	0.37	0.29	0.23
Boat	0	125	42	21	0	0.2	0.22	0.05
Cosmetic Procedures	0	170	32	1	0	0.27	0.17	0
Engagement Ring Financing	0	260	54	86	0	0.41	0.28	0.19
Green Loans	0	80	29	36	0	0.13	0.15	0.08
Household Expenses	0	2,140	493	632	0	3.4	2.56	1.38
Large Purchase	0	857	350	659	0	1.36	1.82	1.44
Medical / Dental	0	1,604	362	664	0	2.55	1.88	1.45
Motorcycle	0	402	87	52	0	0.64	0.45	0.11
RV	0	85	22	26	0	0.14	0.11	0.06
Taxes	0	864	187	260	0	1.37	0.97	0.57
Vacation	0	926	220	253	0	1.47	1.14	0.55
Wedding Loans	0	774	227	334	0	1.23	1.18	0.73

Table 2. Summary Statistics for Originated Loans

Panel A of the table reports the means and standard deviations of the loan terms, loan performance, and borrower characteristics for the loans originated by Prosper in each the four subperiods described in Section 2 and summarized in Figure 1. These subperiods reflect Prosper's major changes in its lending processes during our sample period. Panel B reports the distributions of loan performance statuses, credit score buckets, and loan purposes for these loans. Appendix A contains the definitions of all variables.

Panel A: Loan terms, loan performance, and borrower characteristics

	subperiod 1 7,443 loans (22/day)		**subperiod 2 33,852 loans (40/day)**		**subperiod 3 12,816 loans (87/day)**		**subperiod 4 27,143 loans (156/day)**	
VARIABLE	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Default	0.165	0.371	0.232	0.422	0.172	0.377	0.172	0.377
Unpaid_Principal	0.101	0.258	0.155	0.312	0.125	0.277	0.119	0.269
Loan_Rate	0.208	0.097	0.223	0.076	0.188	0.061	0.168	0.058
Loan_Amount	4669	3815	7850	5358	10292	6525	11355	6701
Maturity5Y	0.004	0.062	0.267	0.442	0.456	0.498	0.331	0.471
Home	0.525	0.499	0.526	0.499	0.563	0.496	0.522	0.5
DTI	0.221	0.139	0.242	0.151	0.255	0.125	0.259	0.113
MissingDTI	0.113	0.316	0.106	0.308	0.059	0.235	0.065	0.247
Income	5236	3899	5724	11528	6178	4003	6189	4227
Bankcard_Utilization	0.511	0.337	0.536	0.316	0.582	0.279	0.612	0.273
Creditlines_7Years	25.79	14.032	26.866	13.705	29.19	12.641	28.524	12.594
Open_creditlines	8.464	4.723	8.655	4.882	10.307	4.752	10.523	4.833
current_delinquencies	0.282	1.062	0.412	1.233	0.352	1.198	0.213	0.885
delinquencies_7years	2.695	7.719	3.896	9.485	3.67	9.368	3.621	9.506
Inquiries_6months	1.01	1.522	1.098	1.553	0.788	1.248	0.865	1.192
public_records_10years	0.216	0.57	0.282	0.64	0.279	0.63	0.314	0.692
public_records_12months	0.01	0.106	0.014	0.133	0.008	0.197	0.004	0.066
Credit_History	185.9	90.2	209.2	93.1	227.3	92.9	223.1	95.2
Employed	0.886	0.318	0.882	0.323	0.912	0.283	0.883	0.322
Emp_Length	6.945	6.873	8.15	7.834	9.548	8.428	9.179	8.457
Prior_Prosper_Loans	0.454	0.687	0.438	0.784	0.376	0.795	0.172	0.583
Partial_Funding			0.744	0.437	0.792	0.406	0.963	0.188
Group_Affiliation	0.096	0.294	0.032	0.176	0.013	0.114	0.007	0.085
Des_Dummy	0.999	0.028	0.802	0.398	0.706	0.456		
Des_Length	142.26	83.92	78.03	55.11	60.16	55.67		
Des_Index	3.395	1.618	2.310	1.627	1.696	1.564		
#Investors	137.95	122.14	87.58	89.18	59.38	98.91	32.14	76.09
Funding_Time	148.89	71.39	87.65	100.38	15.99	45.45	5.42	24.93
1(Fractional)					0.499	0.498	0.310	0.417
1(Whole-Active)					0.501	0.500	0.408	0.491
1(Whole-Passive)							0.282	0.450

Panel B: Distribution of loan statuses, credit scores, and intended loan purposes

	# of obs in each subperiod				% of obs in each subperiod			
	1	2	3	4	1	2	3	4
Loan Status								
Chargeoff	735	4,838	474	908	9.88	14.29	3.7	3.35
Completed	6,213	25,536	9,181	19,765	83.47	75.43	71.64	72.97
Current	0	460	1,444	2,685	0	1.36	11.27	9.91
Defaulted	495	3,018	1,717	3,727	6.65	8.92	13.4	13.76
ScoreX								
<600	0	0	0	389	0	0	0	1.43
600-619	233	650	127	700	3.13	1.92	0.99	2.58
620-639	285	1,066	263	1,847	3.83	3.15	2.05	6.8
640-649	503	1,149	402	1,415	6.76	3.39	3.14	5.21
650-664	795	2,943	814	2,307	10.68	8.69	6.35	8.5
665-689	1,084	6,743	2,194	4,100	14.56	19.92	17.12	15.11
690-701	449	3,309	1,110	2,108	6.03	9.77	8.66	7.77
702-723	942	5,304	2,184	3,938	12.66	15.67	17.04	14.51
724-747	975	4,960	2,147	3,836	13.1	14.65	16.75	14.13
748-777	981	4,027	2,050	3,606	13.18	11.9	16	13.29
778+	1,196	3,701	1,525	2,897	16.07	10.93	11.9	10.67
Intended Loan Purpose								
Debt Consolidation	3,486	16,962	9,054	21,534	46.84	50.11	70.65	79.34
Home Improvement	704	3,642	1,045	1,144	9.46	10.76	8.15	4.21
Business	746	3,042	518	789	10.02	8.99	4.04	2.91
Student use	269	0	0	0	3.61	0	0	0
Auto / Motorcycle / RV / Boat	409	1,292	173	246	5.5	3.82	1.35	0.91
Other	1,829	4,520	678	1,748	24.57	13.35	5.29	6.44
Baby & Adoption	0	99	35	55	0	0.29	0.27	0.2
Boat	0	49	20	10	0	0.14	0.16	0.04
Cosmetic Procedures	0	68	14	0	0	0.2	0.11	0
Engagement Ring Financing	0	136	25	38	0	0.4	0.2	0.14
Green Loans	0	33	9	13	0	0.1	0.07	0.05
Household Expenses	0	1,188	328	381	0	3.51	2.56	1.4
Large Purchase	0	355	178	304	0	1.05	1.39	1.12
Medical / Dental	0	838	250	358	0	2.48	1.95	1.32
Motorcycle	0	211	56	27	0	0.62	0.44	0.1
RV	0	33	8	10	0	0.1	0.06	0.04
Taxes	0	546	128	162	0	1.61	1	0.6
Vacation	0	433	157	135	0	1.28	1.23	0.5
Wedding Loans	0	405	140	189	0	1.2	1.09	0.7

Table 3. The Distribution of Interest Rates

Panel A (Panel B) of the table reports the means and standard deviations of interest rates on funded loans for Prosper's credit ratings (credit score buckets) in each the four subperiods. Prosper switched the primary credit scores it uses from Experian ScoreX PLUS to TransUnion FICO in subperiod 4, hence the statistics reported below are based on ordinal buckets of TransUnion FICO score in subperiod 4.

	% of obs in each subperiod				Mean				Standard Deviation			
	subperiod 1	subperiod 2	subperiod 3	subperiod 4	subperiod 1	subperiod 2	subperiod 3	subperiod 4	subperiod 1	subperiod 2	subperiod 3	subperiod 4
Panel A. Prosper's credit ratings												
AA	5.79	5.16	4.62	6.74	0.084	0.085	0.078	0.074	0.018	0.017	0.007	0.008
A	8.95	13.2	18.16	19.65	0.103	0.119	0.117	0.111	0.019	0.021	0.012	0.012
B	4.35	15.22	24.65	22.54	0.146	0.169	0.159	0.144	0.019	0.022	0.013	0.01
C	9.67	16.55	23.96	29.66	0.204	0.212	0.202	0.18	0.036	0.023	0.015	0.013
D	20.08	21.7	16.1	11.26	0.262	0.256	0.244	0.222	0.034	0.019	0.014	0.014
E	8.25	11.87	10.33	8.2	0.32	0.306	0.283	0.274	0.041	0.017	0.013	0.013
HR	42.91	16.31	2.18	1.95	0.324	0.317	0.313	0.307	0.045	0.002	0.001	0.007
Panel B. Credit score buckets												
600-619	2.29	1.24	0.83	11.79	0.314	0.283	0.288	0.231	0.052	0.039	0.017	0.053
620-639	3.08	2.13	1.59	20.61	0.309	0.277	0.276	0.194	0.05	0.041	0.023	0.052
640-649	9.81	3.11	2.91	20.46	0.275	0.281	0.25	0.172	0.062	0.039	0.031	0.049
650-664	13.79	8.22	5.89	18.88	0.279	0.248	0.234	0.154	0.062	0.055	0.037	0.043
665-689	17.46	18.81	16.6	13.25	0.27	0.254	0.223	0.139	0.063	0.062	0.047	0.039
690-701	7.25	9.52	8.43	6.63	0.258	0.246	0.205	0.123	0.075	0.065	0.05	0.037
702-723	12.81	15.41	16.71	3.83	0.205	0.235	0.192	0.108	0.09	0.067	0.05	0.033
724-747	11.5	14.87	16.8	2.38	0.163	0.204	0.17	0.096	0.081	0.071	0.053	0.03
748-777	10.58	13.09	16.39	1.46	0.139	0.184	0.151	0.085	0.068	0.072	0.05	0.026
778+	11.42	13.59	13.85	0.73	0.113	0.137	0.127	0.078	0.052	0.066	0.048	0.02

Table 4. Explanatory Power of Hard Information for Interest Rates

This table reports OLS regressions of the contractual loan interest rate for funded loans (*Loan_Rate*) on various sets of hard information. In Panel A (B), the model includes only indicators for Prosper credit ratings (credit score buckets). In Panel C and D, the models also include the loan terms and loan applicant characteristics listed below *Loan_Rate* and above *Partial_Funding* in Table 2, as well as indicators for intended loan purposes. Prosper switched the primary credit scores it uses from Experian ScoreX PLUS to TransUnion FICO in subperiod 4. Prosper also changed the set of intended loan purposes in subperiod 2, eliminating "Student use" and adding 13 other purposes. To maintain comparability, we reclassify "Student Use" in subperiod 1 and the 13 new loan purposes added in subperiod 2 as "Other".

Panel A: Credit ratings	(1) subperiod 1	(2) subperiod 2	(3) subperiod 3	(4) subperiod 4
Credit Ratings	Yes	Yes	Yes	Yes
Observations	7,443	33,852	12,816	27,143
R-squared	0.887	0.940	0.955	0.957
Panel B: Credit score buckets				
	subperiod 1	subperiod 2	subperiod 3	subperiod 4
Credit Score Buckets	Yes	Yes	Yes	Yes
Observations	7,443	33,852	12,816	27,143
R-squared	0.497	0.284	0.392	0.371
Panel C: Credit ratings, loan terms, and borrower characteristics				
VARIABLES	subperiod 1	subperiod 2	subperiod 3	subperiod 4
Credit Ratings	Yes	Yes	Yes	Yes
Other Standard Variables	Yes	Yes	Yes	Yes
Loan Purpose	Yes	Yes	Yes	Yes
Observations	7,443	33,852	12,816	27,143
R-squared	0.902	0.966	0.962	0.958
Panel D: Credit score buckets, loan terms, and borrower characteristics				
VARIABLES	subperiod 1	subperiod 2	subperiod 3	subperiod 4
Credit Score Buckets	Yes	Yes	Yes	Yes
Other Standard Variables	Yes	Yes	Yes	Yes
Loan Purpose	Yes	Yes	Yes	Yes
Observations	7,443	33,852	12,816	27,143
R-squared	0.595	0.602	0.639	0.635

Table 5. Predictive Power of Interest Rates for Loan Default

Panel A of the table reports logistic regressions of an indicator for loan default (*Default*) on the contractual interest rate (*Loan_Rate*) on funded loans listed in each the four subperiods. The panel also reports the area under the receiver operating characteristic curve (AUC), as well as Chi-square tests of the differences in AUC between subperiod 1 and subperiods 2-4. Panel B (C) reports the same analyses for the subsamples of loans with poor Prosper credit ratings of C, D, E, or HR (good Prosper credit ratings of AA, A, or B) in each subperiod. Panel C also reports Chi-square tests of the differences in AUCs for loans with good versus poor credit ratings in each subperiod.

Panel A: Overall sample				
VARIABLES	subperiod 1	subperiod 2	subperiod 3	subperiod 4
Loan_Rate	6.4051***	7.0463***	7.2398***	7.6048***
	(18.188)	(37.207)	(18.526)	(27.991)
AUC	0.6689	0.6390	0.6279	0.6374
Compared to subperiod 1				
Chi2		11.79***	16.59***	12.22***
p-value		0.0005	0.0001	0.0005
Economic Magnitude		82.3%	75.7%	81.3%
Observations	7,443	33,852	12,816	27,143
Pseudo R2	0.0543	0.0415	0.0302	0.0316
Panel B: Loans with poor ratings				
VARIABLES	subperiod 1	subperiod 2	subperiod 3	subperiod 4
Loan_Rate	5.9531***	5.9524***	3.9760***	3.5053***
	(9.258)	(17.095)	(5.192)	(7.707)
AUC	0.5949	0.5720	0.5432	0.5472
Compared to subperiod 1				
Chi2		4.66**	16.03***	17.70***
p-value		0.031	0.000	0.000
Economic Magnitude		75.9%	45.5%	49.7%
Observations	4,500	22,234	6,694	14,096
Pseudo R2	0.0192	0.0114	0.00378	0.00386
Panel C: Loans with good ratings				
VARIABLES	subperiod 1	subperiod 2	subperiod 3	subperiod 4
Loan_Rate	13.5926***	15.0957***	14.9933***	15.9171***
	(6.773)	(19.705)	(9.935)	(13.276)
AUC	0.6162	0.6549	0.6151	0.6084
Compared to subperiod 1				
Chi2		4.09**	0.00	0.16
p-value		0.043	0.9596	0.6897
Economic Magnitude		133%	99.1%	93.3%
Compared to loans with poor ratings in the same subperiod				
Chi2	1.09	103.05***	28.31***	42.26***
p-value	0.297	0.000	0.000	0.000
Economic Magnitude	122%	215%	266%	229%
Observations	2,943	11,618	6,122	13,047
Pseudo R2	0.0256	0.0445	0.0246	0.0213

Table 6. Placebo Test (Lending Club)

Panel A reports the means and standard deviations of the interest rates on Lending Club (LC) loans. LC is the largest peer-to-peer lender and Prosper's main competitor. Unlike Prosper, LC has used a proprietary credit-ratings model to pre-set interest rates throughout its life. LC reports seven credit ratings, with A (G) indicating the lowest (highest) credit risk. Panel B reports logistic regressions of an indicator for loan default on interest rates in each of the four subperiods defined based on the changes in Prosper's lending processes. Panel B also reports the area under the receiver operating characteristic curve (AUC), as well as Chi-square tests of the differences in AUCs of subperiod 1 and subperiods 2-4.

Panel A: Distribution of interest rates

	Mean				**Standard deviation**			
LC credit ratings	subperiod 1	subperiod 2	subperiod 3	subperiod 4	subperiod 1	subperiod 2	subperiod 3	subperiod 4
A	0.074	0.075	0.076	0.078	0.009	0.010	0.011	0.010
B	0.110	0.119	0.116	0.118	0.009	0.013	0.012	0.013
C	0.135	0.152	0.155	0.153	0.006	0.012	0.011	0.009
D	0.153	0.181	0.187	0.185	0.005	0.011	0.008	0.010
E	0.169	0.204	0.216	0.219	0.006	0.015	0.007	0.010
F	0.187	0.224	0.239	0.243	0.005	0.015	0.007	0.006
G	0.206	0.236	0.254	0.259	0.005	0.015	0.005	0.001
FICO score buckets								
660-679	0.158	0.171	0.170	0.163	0.019	0.032	0.038	0.040
680-699	0.139	0.148	0.154	0.150	0.019	0.032	0.040	0.040
700-719	0.123	0.127	0.136	0.133	0.022	0.034	0.041	0.040
720-739	0.102	0.106	0.121	0.118	0.023	0.032	0.040	0.039
740-759	0.092	0.092	0.105	0.104	0.023	0.029	0.038	0.036
760-779	0.084	0.083	0.094	0.096	0.021	0.028	0.037	0.035
780+	0.083	0.077	0.085	0.088	0.021	0.025	0.032	0.031

Panel B: Predictive power of interest rates for loan default

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Poor credit rating				**Good credit rating**			
VARIABLES	subperiod 1	subperiod 2	subperiod 3	subperiod 4	subperiod 1	subperiod 2	subperiod 3	subperiod 4
Loan_Rate	14.172***	10.759***	11.660***	7.474***	18.251***	14.528***	17.574***	17.214***
	(4.942)	(15.722)	(14.432)	(11.909)	(13.015)	(38.846)	(29.697)	(34.704)
AUC	0.5606	0.5628	0.5739	0.5505	0.6204	0.6214	0.6345	0.6314
Compare AUC relative to AUC in subperiod 1								
Chi2		0.03	0.95	0.58		0.01	2.35	1.52
p-value		0.867	0.330	0.4473		0.9078	0.126	0.2183
Economic Magnitude		103.6%	121.9%	83.3%		100.8%	111.7%	109.1%
Observations	3,161	23,812	15,525	21,795	10,604	80,313	39,688	60,503
Pseudo R2	0.00726	0.00897	0.0119	0.00577	0.0261	0.0270	0.0336	0.0310

Table 7. Partitioning on the Extent of Soft Information

This table examines how the predictive power of interest rates for loan default varies with the extent of soft information provided by loan applicants, as proxied by above- versus below-median length of loan descriptions (loan description disclosure index) in Panel A (B). This analysis is limited to loans in the fractional loan channel, because we cannot obtain descriptions for loans in the whole loan channel, and subperiods 1 to 3, because Prosper disallows loan applicants to provide loan descriptions in subperiod 4. The panels report logistic regressions of an indicator for loan default on the interest rate on Prosper loans listed in each subperiod partitioned by one of the proxies for soft information. The panels also report the area under the receiver operating characteristic curve (AUC), as well as Chi-square tests of the differences in AUCs between loans with above- versus below-median soft information in the same subperiod and loans with above-median soft information in subperiod 1 versus subperiods 2 and 3.

Panel A: Partitioning on the length of loan descriptions

Loans with poor ratings						
	Long Description			**Short or No Description**		
VARIABLES	Subperiod 1	Subperiod 2	Subperiod 3	Subperiod 1	Subperiod 2	Subperiod 3
AUC	0.6149	0.5783	0.5697	0.5760	0.5672	0.5569
Compared to loans with short or no descriptions in the same subperiod						
Chi2	3.90**	1.73	0.28			
p-value	0.048	0.189	0.599			
Compared to loans with long descriptions in subperiod 1						
Chi2		5.51**	3.76*		0.35	0.83
p-value		0.019	0.052		0.551	0.361
Observations	2,256	10,992	1,584	2,217	10,624	1,687
Loans with good ratings						
	Long Description			**Short or No Description**		
VARIABLES	Subperiod 1	Subperiod 2	Subperiod 3	Subperiod 1	Subperiod 2	Subperiod 3
AUC	0.6201	0.6478	0.6736	0.6174	0.6631	0.6339
Compared to loans with short or no descriptions in the same subperiod						
Chi2	0.01	1.17	1.77			
p-value	0.932	0.279	0.184			
Compared to loans with long descriptions in subperiod 1						
Chi2		0.92	2.40		3.24*	0.29
p-value		0.337	0.121		0.072	0.592
Observations	1,478	5,911	1,450	1,463	5,602	1,629

Panel B: Partitioning on the disclosure index

Loans with poor ratings						
	Detailed description			**Brief or no description**		
VARIABLES	Subperiod 1	Subperiod 2	Subperiod 3	Subperiod 1	Subperiod 2	Subperiod 3
AUC	0.6061	0.5779	0.5571	0.5613	0.5635	0.5638
Compared to loans with brief or no descriptions in the same subperiod						
Chi2	2.88**	2.77*	0.08			
p-value	0.032	0.096	0.779			
Compared to loans with detailed descriptions in subperiod 1						
Chi2		4.54**	5.52**		0.01	0.01
p-value		0.033	0.019		0.907	0.918
Observations	3,075	13,418	1,863	1,398	8,198	1,408

Loans with good ratings						
	Detailed description			**Brief or no description**		
VARIABLES	Subperiod 1	Subperiod 2	Subperiod 3	Subperiod 1	Subperiod 2	Subperiod 3
AUC	0.6146	0.6549	0.6615	0.6216	0.6614	0.6397
Compared to loans with brief or no descriptions in the same subperiod						
Chi2	0.04	0.21	0.50			
p-value	0.848	0.649	0.478			
Compared to loans with detailed descriptions in subperiod 1						
Chi2		2.72	2.55		1.65	0.23
p-value		0.100	0.111		0.199	0.631
Observations	1,865	7,266	1,851	1,076	4,247	1,228

Table 8. Improvement in Transaction Processing Efficiency

This table reports evidence on the benefits of transaction processing efficiency by comparing Prosper to Lending Club (LC) in a 6-month window centered around Prosper's key policy changes. We measure transaction processing efficiency by daily application volume (dollar amount of applications), loan origination (dollar amount of funded loans), and median delay from application to loan origination in days. We aggregate applications or loans by application date to daily observations for Prosper and LC, respectively, and then take natural logarithm to mitigate skewness and simplify the interpretations. Panel A examines the switch from the auction model to the pre-set pricing model, Panel B investigates the impact of adding the whole loan channel, and Panel C focuses on the elimination of loan descriptions. *Prosper* is a dummy variable indicating Prosper as opposed to LC, and *Post* is a dummy variable indicating days after the policy change. We control for day-of-week fixed effects and cluster standard errors by application date. ***, **, and * stand for statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Switching to pre-set pricing model			
VARIABLES	Daily-Applications	Daily-Loans	Daily-Delay
Prosper	-0.728***	-1.507***	1.105***
	(0.038)	(0.050)	(0.044)
Post	0.039	0.203***	-0.142***
	(0.040)	(0.046)	(0.034)
Prosper*Post	-0.626***	0.139*	-0.315***
	(0.065)	(0.076)	(0.056)
Fixed Effects	Day-of-Week	Day-of-Week	Day-of-Week
Observations	362	362	362
R-squared	0.768	0.794	0.790
Panel B: Add whole loan channel			
VARIABLES	Daily-Applications	Daily-Loans	Daily-Delay
Prosper	-2.201***	-2.338***	0.452***
	(0.051)	(0.056)	(0.031)
Post	0.250***	0.251***	0.045
	(0.030)	(0.030)	(0.037)
Prosper*Post	0.306***	0.424***	-0.173***
	(0.057)	(0.063)	(0.043)
Fixed Effects	Day-of-Week	Day-of-Week	Day-of-Week
Observations	362	362	362
R-squared	0.939	0.933	0.475
Panel C: Disallow loan descriptions			
VARIABLES	Daily-Applications	Daily-Loans	Daily-Delay
Prosper	-1.807***	-1.778***	0.106***
	(0.024)	(0.027)	(0.029)
Post	0.170***	0.183***	-0.310***
	(0.026)	(0.027)	(0.030)
Prosper*Post	0.472***	0.332***	0.262***
	(0.044)	(0.048)	(0.038)
Fixed Effects	Day-of-Week	Day-of-Week	Day-of-Week
Observations	362	362	362
R-squared	0.931	0.925	0.494

Table 9. Diversification Effects

This table reports the predictive power of loan interest rates for loan performance for portfolios of 1, 5, 10, or 20 randomly selected Prosper loans with the same credit rating listed in the same subperiod. Panel A reports the area under the receiver operating characteristic curve (AUC) for logistic regressions of an indicator for the occurrence of one or more loan defaults in the portfolio on the (loan amount) weighted-average interest rate, as well as Chi-square tests of the differences in the AUCs in subperiod 1 versus subperiods 2-4. Panel B presents the R^2s of OLS regressions of the weighted-average proportion of unpaid principal on the weighted-average contractual loan interest rate in the portfolio.

Panel A: Predictive power of interest rates for loan default in the portfolio				
VARIABLES	subperiod 1	subperiod 2	subperiod 3	subperiod 4
5-loan portfolios				
AUC	0.7153	0.7116	0.6803	0.7085
Compare AUC relative to AUC in subperiod 1				
Chi2		0.06	3.82*	0.19
p-value		0.811	0.051	0.663
10-loan portfolios				
AUC	0.7936	0.8151	0.7630	0.7710
Compare AUC relative to AUC in subperiod 1				
Chi2		0.94	1.22	0.99
p-value		0.332	0.269	0.319
20-loan portfolios				
AUC	0.8390	0.8993	0.8720	0.8436
Compare AUC relative to AUC in subperiod 1				
Chi2		1.87	0.41	0.01
p-value		0.171	0.521	0.916
Panel B: Explanatory power of interest rates for the proportion of unpaid principal				
VARIABLES	subperiod 1	subperiod 2	subperiod 3	subperiod 4
Single loan				
R-Squared	0.048	0.045	0.031	0.039
5-loan portfolios				
R-Squared	0.135	0.125	0.100	0.140
10-loan portfolios				
R-Squared	0.212	0.209	0.167	0.240
20-loan portfolios				
R-Squared	0.327	0.334	0.248	0.364

Table 10. Fractional Loan Channel versus Whole Loan Channel

Panels A-C of this table report the predictive power of contractual loan interest rates for default on of loans listed in subperiod 3. Panel A reports the area under the receiver operating characteristic curve (AUC) and Chi-square tests comparing the fractional and active whole loan channels, separately for all loans, loans with poor credit ratings, and loans with good credit ratings. We exclude loans with credit ratings of "AA", because no whole loan has this rating. Panel B (C) reports AUCs and Chi-square tests analogous to those in Panel A but splitting fractional loans into above- versus below-median length loan description (loan description disclosure index). Panel D reports AUCs and Chi-square tests analogous to those in Panel A but in the fractional loan channel, the active whole loan channel, and passive whole loan channel and also in subperiod 4.

Panel A: Compare fractional loans to active whole loans in subperiod 3

	All loans		Loans with poor ratings		Loans with good ratings	
VARIABLES	Fractional	Whole-Active	Fractional	Whole-Active	Fractional	Whole-Active
AUC	0.6243	0.6059	0.5719	0.5260	0.6039	0.5726
Compared to active whole loans in same credit-rating category						
Chi2	2.11		7.46***		1.91	
p-value	0.146		0.006		0.167	
Observations	5,776	6,421	3,295	3,399	2,481	3,022

Panel B: Split fractional loans in subperiod 3 by the length of loan descriptions

	Loans with poor ratings			Loans with good ratings		
VARIABLES	Fractional & Long	Fractional & Short	Whole-Active	Fractional & Long	Fractional & Short	Whole-Active
AUC	0.5662	0.5559	0.5260	0.6115	0.5973	0.5726
Compared to active whole loans same in same credit rating category						
Chi2	3.59*	2.19		1.99	0.74	
p-value	0.058	0.139		0.159	0.390	
Observations	1,711	1,584	3,399	1,297	1,184	3,022

Panel C: Split fractional loans in subperiod 3 by the disclosure index

	Loans with poor ratings			Loans with good ratings		
VARIABLES	Fractional & Detailed	Fractional & Brief	Whole-Active	Fractional & Detailed	Fractional & Brief	Whole-Active
AUC	0.5602	0.5542	0.5260	0.6106	0.5948	0.5726
Compared to whole loans						
Chi2	2.73*	1.83		2.13	0.50	
p-value	0.099	0.178		0.145	0.481	
Observations	1,894	1,401	3,399	1,550	931	3,022

Panel D: Compare fractional loans to active and passive whole loans in subperiod 4

	Loans with poor ratings			Loans with good ratings		
VARIABLES	Fractional	Whole-Active	Whole-Passive	Fractional	Whole-Active	Whole-Passive
AUC	0.5427	0.5419	0.5598	0.5804	0.5788	0.5771
Compared to fractional loans						
Chi2		0.00	1.24		0.01	0.02
p-value		0.952	0.266		0.934	0.877
Compared to loans in the same channel and within subperiod 3						
Chi2	1.36	1.16		1.08	0.10	
p-value	0.243	0.282		0.299	0.748	
Observations	4,764	5,735	3,597	2,642	4,879	3,755

Appendix A. Variable Definitions

Variable	**Definition**
List_Rate	Interest rate in the loan request. *List_Rate* may differ from *Loan_Rate* under the auction regime.
List_Amount	Dollar amount of the loan request. *List_Amount* differs from *Loan_Amount* in two cases: (1) *Loan_Amount* is missing for unfunded loan requests; (2) *List_Amount* is larger than *Loan_Amount* for partially funded loans in subperiods 2 to 4.
Loan_Rate	Contractual interest rate for funded loan.
Loan_Amount	Dollar amount of funded loan.
Maturity5Y	Indicator for loan term of 5 years.
Home	Indicator for home-owning borrower.
DTI*	Debt-to-income ratio of loan applicant. Missing values are replaced with -1.
MissingDTI*	Missing or invalid debt-to-income ratio.
Ln(Income)	Natural logarithm of borrower's stated monthly income.
Bankcard_Utilization*	Percentage of available revolving credit utilized by borrower.
Creditlines_7Years*	Number of credit lines for borrower in prior seven years.
Open_creditlines*	Number of current open credit lines.
Ln(Amt_Delinquencies)*	Natural logarithm of one plus the dollar amount of the borrower's delinquent accounts.
Ln(current_delinquencies)*	Natural logarithm of one plus the borrower's current number of delinquent accounts
Ln(delinquencies_7years)*	Natural logarithm of one plus the borrower's number of deliquent accounts delinquent in the past 7 years at the time the credit profile was pulled.
Inquiries_6months*	Number of credit inquiries for the borrower made during the past six months.
Ln(public_records_10years)*	Natural logarithm of one plus the borrower's number of public records in the past 12 months.
Ln(public_records_12months)*	Natural logarithm of one plus the borrower's number of public records in the past 10 years.
Credit_History*	Number of months since the borrower's first recorded credit line at the time of loan origination.
Employed	Indicator for employed borrowers.
Emp_Length	Length of the the borrower's current employment at the listing of the loan request.
Prior_Prosper_Loans	Number of the borrower's prior loans originated on Prosper's platform.
Default	Indicator for loans that default, are charged off, or are current but more than 90 days delinquent.
Prosper Rating	Prosper's proprietary credit rating. The ratings take values of AA, A, B, C, D, E, and HR. AA (HR) denotes the lowest (highest) risk.
Credit Score*	Credit score buckets (eleven, with a width of 15 or 20 points) provided by a consumer credit reporting agency. Prosper provides Experian ScoreX PLUS throughout the sample period and TransUnion FICO Score for loan requests made since January 25, 2013. Prosper began to use FICO score in its credit-rating model in September 2013.
Partial_Funding	Indicator for borrowers that elect partial funding in subperiods 2 to 4. Borrowers electing the option can obtain a loan if funding bids exceed 70% of *List_Amount*.
Group_Affiliation	Indicator for borrowers affiliated with a social networking group on Prosper.com.
Des_Dummy	Indicator for borrowers that provide textual loan descriptions. This variable is only available for loan requests that are listed in prospectus supplements filed with the SEC (i.e., are not withdrawn by borrowers prior to listing on Prosper's lending platform or are listed in the whole loan channel).
Des_Length	Number of words in loan descriptions. Zero if the loan request does not include a loan description.
Des_Index	Number of the following topics in loan description: purpose of the loan, family life or family members, prior loans with Prosper, credit profile details, job prospects, monthly income, monthly expenses, explanations for negative information in the credit profile, and pleading lenders for help. Identified by a supervised machine learning algorithm. Zero if the loan request does not include a loan description.

FC_per_Request	Funding offered by peer lenders divided by *List_Amount*. Ranges from 0 to 1. In subperiod 1 (subperiods 2–4), funding offered is less than 100% (70%) of *List_Amount* cannot yield loan originations.
Funding_Time	Number of hours from the loan listing on Prosper's lending platform to the end of bidding (i.e., until the loan request is funded, cancelled by Prosper, withdrawn by the borrower, or expires)
#Investors	Number of investors successfully funding the loan. Only available for loan requests that yield funded loans.
1(Fractional)	Indicator for loan requests intially allocated to the fractional loan channel.
1(Whole-Active)	Indicator for loan requests initially allocated to the active whole loan channel. Prosper launched this channel at the beginning of subperiod 3.
1(Whole-Passive)	Indicator for loan requests initially allocated to the passive whole loan channel. Prosper launched this channel in November 2013.

All indicator variables take a value of one if the condition is present and zero otherwise. Prosper determines variable denoted by * at the time it pulls borrowers' credit profiles.

Appendix B. Sample Loan Request

The following loan request, listed on August 27, 2009, is available at
https://www.sec.gov/Archives/edgar/data/1416265/000141626509000124/listing_20090827-1642.htm

Borrower Payment Dependent Notes Series 422165

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:	**$1,600.00**	Prosper Rating:	**C**		
Term:	**36 months**	Estimated loss:	**6.5%**		
Starting lender yield:	**27.00%**	Starting borrower rate/APR:	**28.00% / 30.45%**	Starting monthly payment:	**$66.18**
Auction yield range:	**8.23% - 27.00%**	Estimated loss impact:	**7.15%**		
Lender servicing fee:	**1.00%**	Estimated return:	**19.85%**		

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 above 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:	**9**	First credit line:	**Aug-1993**	Debt/Income ratio:	**21%**
Credit score:	**640-660 (Aug-2009)**	Current / open credit lines:	**8 / 8**	Employment status:	**Full-time employee**
Now delinquent:	**0**	Total credit lines:	**53**	Length of status:	**1y 1m**
Amount delinquent:	**$0**	Revolving credit balance:	**$0**	Occupation:	**Social Worker**
Public records last 12m / 10y:	**1/ 1**	Bankcard utilization:	**0%**	Stated income:	**$25,000-$49,999**
Delinquencies in last 7y:	**26**	Homeownership:	**No**		
Inquiries last 6m:	**1**				
Screen name:	**gentle-trade**	Borrower's state:	**Michigan**	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.

Description

PAYING OFF PAYDAY LOANS

Purpose of loan:
This loan will be used to pay off high interest loans that I took out to help my family.

My financial situation:
I am a good candidate for this loan because I have learned how to budget money despite some mistakes in my past (a bankruptcy).? I have late payments in the past because I was trying to sell a house and the lender recomeded that I stop making payments so that I could?qualify for a short sale.?Looking back this may not have been the best course of action as it eventually led to my bankruptcy filing.

I am a very responsible?person and?I? am very careful with my financial decisons.? I was unable to qualify for a tradtional loan due to the bankruptcy and that is why I turned to the pay day loans.? I have a great job and good steady income.? I am able to make monthly payments if someone could give me a chance.?

Monthly net income: $ 3778

Monthly expenses: $
??Housing: $ 550
??Insurance: $ 250
??Car expenses: $ 309
??Utilities: $ 100
??Phone, cable, internet: $ 200
??Food, entertainment: $ 50
??Clothing, household expenses $ 50
??Credit cards and other loans: $ 630 (payday loan payments)
??Other expenses: $

Information in the Description is not verified.

Appendix C. Soft Information and Funding Outcomes

Panel A reports OLS regressions of funding outcomes (the percentage of the borrower's requested loan amount offered by peer lenders) on two proxies for soft information*:* the natural logarithm of one plus the number of words in loan descriptions [*Ln(Des_Length)*] and the number of topics in loan descriptions (*Des_Index*). The sample is restricted to subperiod 1-3 as loan descriptions are disallowed in subperiod 4. The model includes controls for loan terms and borrower characteristics as well as fixed effects for Experian credit score buckets, loan purposes, and the day of loan listings. The sample includes both successful and failed loan requests, but it excludes requests that are withdrawn by borrowers or cancelled by Prosper within 24 hours after listing to ensure that the funding outcomes reflect peer lenders' decisions. Panel B reports the same regressions separately for loan requests with poor versus good credit ratings and test the coefficient on the soft information variables. Standard errors clustered by list date are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Overall sample						
VARIABLES	subperiod 1	subperiod 2	subperiod 3	subperiod 1	subperiod 2	subperiod 3
Ln(Des_Length)	0.021***	0.008***	0.002**			
	(0.004)	(0.001)	(0.001)			
Des_Index				0.009***	0.009***	0.002**
				(0.001)	(0.001)	(0.001)
Group_Affiliation	0.031***	0.025***	-0.002	0.032***	0.024***	-0.002
	(0.008)	(0.007)	(0.004)	(0.008)	(0.007)	(0.004)
List_Rate	0.398***	-0.165***	0.128***	0.404***	-0.172***	0.126***
	(0.040)	(0.033)	(0.024)	(0.040)	(0.033)	(0.024)
ln(Loan_Amount)	-0.209***	-0.124***	-0.016***	-0.208***	-0.123***	-0.016***
	(0.003)	(0.004)	(0.002)	(0.003)	(0.004)	(0.002)
Maturity5Y	0.209***	0.007*	-0.011***	0.210***	0.007*	-0.011***
	(0.040)	(0.004)	(0.003)	(0.040)	(0.004)	(0.003)
Home	-0.034***	0.015***	0.003	-0.034***	0.015***	0.003
	(0.005)	(0.003)	(0.002)	(0.005)	(0.003)	(0.002)
DTI	-0.483***	-0.028**	0.014*	-0.482***	-0.029**	0.015*
	(0.015)	(0.013)	(0.008)	(0.015)	(0.013)	(0.008)
MissingDTI	-0.772***	-0.050***	0.024**	-0.771***	-0.051***	0.024**
	(0.020)	(0.018)	(0.011)	(0.020)	(0.018)	(0.011)
Ln(Income)	0.012***	0.004***	-0.000	0.012***	0.004***	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Bankcard_Utilization	-0.077***	0.015***	-0.001	-0.077***	0.015***	-0.001
	(0.007)	(0.005)	(0.004)	(0.007)	(0.005)	(0.004)
Open_creditlines	0.004***	0.002***	-0.000	0.004***	0.002***	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Ln(current_delinquencies)	-0.123***	-0.034***	-0.002	-0.123***	-0.034***	-0.002
	(0.005)	(0.004)	(0.002)	(0.005)	(0.004)	(0.002)
Ln(delinquencies_7years)	-0.017***	-0.007***	-0.002	-0.017***	-0.007***	-0.002
	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Inquiries_6months	-0.031***	-0.012***	-0.001	-0.031***	-0.012***	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Ln(public_records_10years)	-0.074***	0.001	0.006***	-0.075***	0.001	0.006***
	(0.006)	(0.004)	(0.002)	(0.006)	(0.004)	(0.002)
Ln(public_records_12months)	0.041*	-0.007	0.015***	0.044*	-0.007	0.015***
	(0.023)	(0.015)	(0.006)	(0.023)	(0.015)	(0.006)
Credit_History	0.000	-0.000***	-0.000***	0.000	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Employed	0.034***	0.064***	0.008	0.033***	0.064***	0.007
	(0.006)	(0.006)	(0.005)	(0.006)	(0.006)	(0.005)
Emp_Length	0.001***	0.000	0.000	0.001***	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Prior_Prosper_Loans	0.076***	0.066***	0.009***	0.074***	0.065***	0.009***
	(0.005)	(0.003)	(0.001)	(0.004)	(0.003)	(0.001)
Credit Score FE	Yes	Yes	Yes	Yes	Yes	Yes
Purpose FE	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	35,444	51,783	7,316	35,444	51,783	7,316
R-squared	0.323	0.250	0.091	0.323	0.250	0.091

Panel B: Loan requests with poor versus good credit ratings

VARIABLES	Period 1	Period 2	Period 3	Period 1	Period 2	Period 3
Loan Requests with Poor Credit Ratings						
Ln(Des_Length)	0.021***	0.007***	-0.000			
	(0.004)	(0.001)	(0.000)			
Des_Index				0.008***	0.008***	0.000
				(0.001)	(0.001)	(0.000)
Other Control	Yes	Yes	Yes	Yes	Yes	Yes
Credit Score FE	Yes	Yes	Yes	Yes	Yes	Yes
Purpose FE	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	28,578	33,734	3,421	28,578	33,734	3,421
R-squared	0.313	0.283	0.051	0.313	0.283	0.051
Loan Requests with Good Credit Ratings						
Ln(Des_Length)	0.002	0.011***	0.003***			
	(0.008)	(0.001)	(0.001)			
Des_Index				0.003	0.009***	0.002
				(0.003)	(0.001)	(0.001)
Other Control	Yes	Yes	Yes	Yes	Yes	Yes
Credit Score FE	Yes	Yes	Yes	Yes	Yes	Yes
Purpose FE	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,866	18,049	3,895	6,866	18,049	3,895
R-squared	0.299	0.292	0.129	0.299	0.290	0.127
Difference of coefficients on Ln(Des_Length) or Des_Index for Loan Requests with Poor versus Good Credit Ratings						
Difference	0.019**	-0.004***	-0.003***	0.005**	-0.001	-0.002
p-value	0.016	0.001	0.008	0.047	0.210	0.121