

# Auction vs. Posted-Price: Market Mechanism, Lender Behaviors, and Transaction Outcomes in Online Crowd-Funding

Zaiyan Wei and Mingfeng Lin<sup>1</sup>

June 2013

## Abstract

Despite its popularity in electronic commerce, auction appears to be losing some appeal to posted-price sales recently, as documented in several studies. Yet, there is little systematic research on how these different market mechanisms affect market participant behaviors and transaction outcomes. In this paper, we exploit an exogenous and surprising regime change on a peer-to-peer micro-lending platform, Prosper.com, to answer this question in the context of crowd-funding. We first develop a stylized model that yields empirically testable hypotheses, then test them using detailed transactions data. Our empirical results support our theoretical predictions about the comparisons of interest rates and funding probabilities. In particular after the regime change, loans are funded with higher probabilities, but the pre-set interest rates under the posted-prices regime tend to be higher than borrower's starting interest rates under auctions. Meanwhile, all else equal, loans funded under the pre-set regime are slightly more likely to default. These results justify Prosper's purposes of switching to the posted-price regime, but also point to some unintended consequences. We also examine the effect of the regime change on lenders' behaviors, such as herding.

**Keywords:** Multiunit auctions, Posted-price, Crowd-funding, Peer-to-peer (P2P) lending, Observational learning

---

<sup>1</sup>Zaiyan Wei: Department of Economics, University of Arizona (Email: [zwei1985@email.arizona.edu](mailto:zwei1985@email.arizona.edu)). Mingfeng Lin: Department of Management Information Systems, University of Arizona, (Email: [mingfeng@eller.arizona.edu](mailto:mingfeng@eller.arizona.edu)). The authors contribute equally in this research. We thank Keisuke Hirano, Christopher Lamoureux, Stanley Reynolds, John Wooders, Mo Xiao for helpful comments and suggestions. All errors remain our own. This is an abbreviated version of the paper prepared for CIST 2013; a full working paper is available from the authors. Comments are welcome and much appreciated.

# 1 Introduction

Auctions have long been a dominant market mechanism in electronic commerce. For instance, eBay.com is one of the earliest and most successful examples for consumer-to-consumer marketplaces built upon auctions. Auctions are also widely used in online business-to-business (B2B) procurements and many other contexts<sup>1</sup>. Researchers have conducted extensive research on auctions even before the Internet age; but it is with the Internet that online auctions are now able to reach millions of potential customers, generating significant interest and success. Naturally, when internet-based crowd-funding markets emerged in the past decade, auctions were often adopted as the typical sales mechanism. In fact, one of the earliest such platforms, Prosper.com, was called the “eBay for personal loans” since it uses an auction mechanism to aggregate bids from investors.

Recently however, an interesting trend has emerged in online markets: Auctions seem to have lost some of their appeal. A notable example can be found on – interestingly – eBay.com. Using proprietary data from eBay.com, [Einav et al. \(2012\)](#) show that eBay sellers increasingly favor the posted-price sales over the open-auctions. Two other studies ([Hammond \(2010\)](#), [Hammond \(2013\)](#)) observe a similar trend. These studies focus on antecedents to the choice between auctions and posted-price, since on eBay.com, such a choice is endogenous to the seller. To date, we still know little about how changing market mechanisms affects the behavior of market participants and transaction outcomes. We study this question in the context of online crowd-funding, exploiting an exogenous change mandated by a market platform.

Specifically, our research focuses on online debt-based crowd-funding, also known as “peer-to-peer” (henceforth “P2P”) lending. This is an online market for unsecured personal loans. On December 20, 2010, Prosper.com<sup>2</sup> surprisingly abandoned its well-known auction model (where each investor bids both a dollar amount and an interest rate) and switched the entire website to a posted-price mechanism ([Gonsalves \(2010\)](#)) (where the interest rate is pre-set and investors only

---

<sup>1</sup>For an early article on auctions in e-commerce, please refer to [Economist \(2000\)](#) which argues for auctions’ value-discovering advantage over other mechanisms. Also see [Lucking-Reiley \(2000\)](#) and [Bajari and Hortaçsu \(2004\)](#) for thorough introductions and literature review of the research on online auctions.

<sup>2</sup>For more information on the Prosper marketplace, please refer to its website: <http://www.prosper.com>, and its Wikipedia page: [http://en.wikipedia.org/wiki/Prosper\\_Marketplace](http://en.wikipedia.org/wiki/Prosper_Marketplace).

bid a dollar amount of the loan)<sup>3</sup>. Compared to the eBay studies where the change is gradual and endogenous, this regime change on Prosper.com is immediate, exogenous and surprising; it therefore provides an ideal opportunity to investigate how different market mechanisms impact participant behaviors and market efficiency.

Understanding how online market mechanisms affect participant behavior and transaction outcome is an important and in fact, fundamental, question for electronic commerce. This is especially true for the nascent but burgeoning industry of online crowd-funding<sup>4</sup>, of which Prosper.com is but one example. Only if we come to a comprehensive understanding of the intended and unintended consequences of market mechanisms in this emerging area of research, can we design a more efficient and effective marketplace to match demand and supply of funds, and ensure its long-term viability. As the US prepares for further growth in this industry, especially the upcoming equity-based crowd-funding legalized by the 2012 “Jumpstart Our Business Startups” (JOBS) Act, our research question has important and timely policy implications as well.

To address this research question, we first propose a model comparing the multiunit uniform price auctions with the posted-price mechanism in the context of P2P lending. To our knowledge, this is the first theoretical comparison of these two market mechanisms<sup>5</sup>. Our model predicts that Prosper.com, as the pricing agent in the posted-price regime, will assign higher interest rates for loans, compared to what the borrowers would have chosen as the reserve interest rates in the auctions. Meanwhile, listings will be funded with higher probability under posted-price sales than auctions.

We then test these hypotheses empirically using data from Prosper.com around the time of the regime change, exploiting the exogenous policy change on the website. We focus on listings initiated during a short time period before and after the regime change, specifically from August 20, 2010 to April 19, 2011. We compare the pricing (the initial interest rate of a listing), funding

---

<sup>3</sup>Prosper.com’s corporate blog about the regime change can be found at <http://blog.prosper.com/2010/12/30/exciting-new-enhancements-at-prosper/>.

<sup>4</sup>See [Agrawal, Catalini and Goldfarb \(2013\)](#) for a thorough review of the literature on crowd-funding, and [Lawton and Marom \(2010\)](#) for the new trend in this market.

<sup>5</sup>[Einav et al. \(2012\)](#) propose a simple model comparing a single object second price auction with the posted-price mechanism, while we focus on the comparison of the multiunit uniform price auction with the posted-price mechanism.

probabilities (how likely a listing will receive full funding, and thus the loan is initiated), as well as the contract interest rates of the funded loans. Consistent with our theoretical predictions, we find that the initial interest rates under the posted-price mechanism are indeed higher than those in the auctions on average, and the listings after the regime change are much more likely to be funded than before. However, we also find that the *contract* interest rates in the posted-price stage are on average lower than in the auction stage. We propose explanations for this intriguing result later in the paper. Overall, there is evidence that the regime change leads to short-term improvement for borrowers.

On the other hand, we also investigate the effect of the mechanism change on lenders' behavior, including herding and bidding strategies. We find that lenders tend to submit larger bids, and submit those bids sooner, under the posted-price regime than in the auctions. This is also consistent with the finding that loans are funded faster for borrowers, and help with "quicker deployment of funds" as intended by Prosper.com. Interestingly however, we find preliminary evidence that all else equal, loans funded in the posted-price stage are associated with slightly *higher* default rates.

Our work contributes to a long-term debate over the optimal sales mechanism, especially the trade-off between auctions and posted-price. Wang (1993) and Kultti (1999) are among the earliest theoretical treatments on the comparison of the single object auctions and the posted price selling<sup>6</sup>. Further comparisons of these market mechanisms can be found in such diverse fields as treasury auctions (Ausubel and Cramton (2002), Hortacsu and McAdams (2010)) and initial public offering (IPO) (Biais, Bossaerts and Rochet (2002), Zhang (2009)). Furthermore, our paper also contributes to the growing literature on crowd-funding in general, and the research on P2P micro-lending in particular. Recent investigations include Zhang and Liu (2012) and Lin, Prabhala and Viswanathan (2013). Our results on lenders' herding behavior contributes to the observational learning literature, as developed theoretically in Banerjee (1992) and Bikhchandani, Hirshleifer and Welch (1992), and empirically as in Simonsohn and Ariely (2008) and Zhang and Liu (2012).

---

<sup>6</sup>For the comparison of auctions with other mechanisms, see Bulow and Klemperer (1996) as an example of auctions versus negotiations.

## 2 Research Context

Since the inception of Zopa.com in 2005 in United Kingdom, online P2P micro-lending has witnessed rapid growth around the globe. In the United States, Prosper.com and LendingClub.com are the two largest platforms. Prosper.com officially opened to the public on February 13, 2006. As of January 16, 2013, there are 1.61 million registered members (either as a borrower, a lender, or both) on Prosper.com. More than 68,022 unsecured personal loans, valued over USD 446 million in total, have been funded.

A brief outline of the funding procedure on Prosper.com is as follows<sup>7</sup>. A potential borrower starts with a loan application to the website by registering on Prosper.com and verifying his identity. After that, the borrower may post an eBay-style listing, describing the purpose of the loan, the requested amount, and the term of the loan (typically 3 years). The initial interest rate can be specified in two ways. Before December 20, 2010 the borrower needs to specify the maximum rate he or she is willing to accept. After the regime change to posted-price (pre-set interest rate), Prosper.com *presets* an interest rate for the borrower based on the borrower's credit history and loan characteristics.

Before the regime change on December 20, 2010, once the listing is posted with a specified maximum duration, a multiunit uniform price auction will be conducted until the listing is either fully funded, or expired. Any verified Prosper.com lender can bid in the auctions. Their bids have to specify the amount of funds that they would like to invest, as well as the minimum interest rate that they are willing to lend at. All lenders can observe previous lenders' identities and their bidding amount, but not necessarily their interest rates. During the bidding process, the ongoing loan interest rate is the lowest rate among all lenders that are outbid (excluded from funding the loan), or the reserve interest rate. Once a lender is outbid, his bidding interest rate will be made public. At the end of the auction process, if the loan receives full funding, the contract interest rate will be the ongoing interest rate at that time, which can be either the lowest losing interest rate or the reserve interest rate. In a sense, the borrower sets the initial interest rate and the auction helps

---

<sup>7</sup>Zhang and Liu (2012) and Freedman and Jin (2008) provide more detailed descriptions.

“discover” the contract interest rate.

On December 20, 2010, Prosper.com surprisingly eliminated this auction model. Since then, the interest rate is preset by Prosper.com based on the borrower’s Prosper rating and characteristics of the loan request (such as the term of the loan). The lenders now only specify the amount of dollars to invest, implicitly accepting the preset interest rate. Loans are originated immediately upon full funding<sup>8</sup>, and the contract interest rate is the rate preset at the beginning. Table 1 summarizes the key difference.

Prosper.com believes that the new posted-price mechanism will allow “...a quicker deployment of funds,” and borrowers will “likely get their loan listing funded sooner as well.”<sup>9</sup> To better understand how these two different mechanisms affect the behavior of market participants and transaction outcomes, especially if there are any unintended consequences, we propose a stylized model to motivate our subsequent empirical analyses.

### 3 A Simple Model

In this section, we develop a model to compare the multiunit uniform price auctions with the posted-price mechanism. This model is based on the share auction model proposed by [Wilson \(1979\)](#), and further developed in [Back and Zender \(1993\)](#) and [Wang and Zender \(2002\)](#). Consistent with this literature, we take the usual commodity economy interpretation such that a higher interest rate is equivalent to a lower “price” of the loan.

We consider a borrower posting a listing on the platform. In an auction, the highest losing bid (or the reserve price) sets the price for all winning lenders. In the posted-price setting, Prosper.com presets the price for a particular loan, and the borrower either accepts or rejects this price offer. Once the borrower accepts the offer and the listing is created, any lender can purchase the loan at the pre-set price. All winning lenders will pay this price.

---

<sup>8</sup>During the time of our study, no partial funding was allowed. If a listing cannot attract enough bids to fund the entirety of the request, the loans will not be originated.

<sup>9</sup>See their blog entry on <http://blog.prosper.com/2010/12/30/exciting-new-enhancements-at-prosper/>.

Consider a borrower interested in borrowing money with cost  $c$  of making the listing. This cost is realized when the loan is successfully funded; otherwise the borrower incurs 0 cost. We assume the borrower is requesting a loan with  $Q$  units, and there are  $N$  potential lenders. We assume that there are always enough lenders, i.e.,  $N \gg Q$ .

We assume that each lender demands at most one unit of the loan, and has an independent private value for the loan. Let  $V_n$  denote the lender  $n$ 's valuation,  $n = 1, 2, \dots, N$ . Let  $v_n$  denote its realization. We assume that  $V_n$  is distributed IID with CDF  $F_V(\cdot)$ , and PDF  $f_V(\cdot)$ . We let  $V^{N:k}$  denote the  $k$ -th highest value among  $N$  IID valuations,  $k = 1, 2, \dots, N$ .  $v^{N:k}$  is its realization. We denote the distribution of  $V^{N:k}$  by  $G_k(\cdot)$  (or PDF  $g_k(\cdot)$ ).

### 3.1 Auctions

We assume a sealed-bid multiunit uniform price auction with single-unit demand. In such an auction the lenders all incur a nonnegative transaction cost,  $\lambda$ . This cost reduces the lenders' valuation to  $V_n - \lambda$ . We can interpret the  $\lambda$  as the difference in transaction costs in the auctions and the posted-price regime. In the private value paradigm, auction theory ([Krishna \(2009\)](#)) predicts that the weakly dominant strategy for a lender is to submit his true value,  $V_n - \lambda$ . Thus, the winners will be the  $Q$  lenders with the highest values, and each of them wins one unit of the loan. The market clearing price is set by the highest losing bid or the borrower's reserve price. Knowing the lenders' bidding strategy, the borrower will choose a reserve price,  $r$ , to maximize his expected profit. In the context of Prosper.com, this reserve price corresponds to the borrower's maximum interest rate set at the very beginning of the auction process.

The borrower's profit is thus  $\pi_A = Q \cdot (p_A(r) - c)$ , where  $p_A(r)$  is the market clearing price if the loan is funded. We let  $P_A(r)$  denote the probability of being funded. It is clear that the market clearing price will vary across listings. To summarize, the market clearing prices will be equal to

$$\begin{cases} v^{N:Q+1} - \lambda, & \text{if } v^{N:Q+1} - \lambda \geq r; \\ r, & \text{if } v^{N:Q} - \lambda \geq r > v^{N:Q+1} - \lambda. \end{cases}$$

Note that the probabilities of being funded are  $\Pr(V^{N:Q+1} - \lambda \geq r)$  and  $\Pr(V^{N:Q} - \lambda \geq r > V^{N:Q+1} - \lambda)$  respectively. Then the expected market clearing price  $p_A(r)$  will be respectively  $E[V^{N:Q+1} - \lambda | V^{N:Q+1} - \lambda \geq r]$  and  $r$ . Therefore, we can write the borrower's expected profit as

$$E\pi_A = Q \cdot \left[ E[V^{N:Q+1} - \lambda | V^{N:Q+1} - \lambda \geq r] - c \right] \cdot \Pr(V^{N:Q+1} - \lambda \geq r) \\ + Q \cdot (r - c) \cdot \Pr(V^{N:Q} - \lambda \geq r > V^{N:Q+1} - \lambda).$$

The borrower maximizes his expected profit by choosing the initial reserve price. It can be shown that the optimal reserve price  $r^*$  satisfies the following equation,

$$r^* = c + \frac{1 - F_V(\lambda + r^*)}{Q \cdot f_V(\lambda + r^*)}. \quad (3.1)$$

The result implies that the optimal reserve price is independent of the number of lenders. If  $V_n$  has a log-concave distribution,  $r^*$  is decreasing with the quantity  $Q$ .

### 3.2 Posted Price

Under the new posted-price regime, Prosper.com presets a fixed price level,  $p$ , to maximize its expected profit. Then the borrower either accepts or rejects this offer. Upon accepting the offer, the borrower will post the listing, and the price will be fixed at the pre-set level. Before we model Prosper.com's decision process, we consider borrower's choice first.

Suppose the borrower gets to choose the fixed price level. In this situation, the borrower's expected profit can be written as  $E\pi_B = Q \cdot (p - c) \cdot \Pr(V^{N:Q} \geq p)$ . The  $B$  subscript indicates that it is now the borrower's choice. The borrower maximizes his revenue by choosing  $p$ . The following equation characterizes this optimal price level,  $p_B^* = c + \frac{1 - G_Q(p_B^*)}{g_Q(p_B^*)}$ . It can be shown that,  $p_B^* > r^*$ . It implies that suppose the borrower chooses the price, he presets a higher level compared to the reserve price he would have chosen in an auction. This comparison is consistent with the finding in [Einav et al. \(2012\)](#).



We now return to Prosper.com's decision. The platform first presets the price  $p$  for a particular loan. Then the borrower's strategy is to pick a threshold or cut-off price  $\tilde{p}$ . If  $p$  is higher than this cut-off, the borrower will accept the offer. If it is lower, he will reject it and leave the market. To summarize, the borrower accepts if  $p \geq \tilde{p}$ , and rejects if  $p < \tilde{p}$ .

Note that again the probability of being funded is  $\Pr(V^{N:Q} \geq p)$ . Then the borrower's expected revenue of accepting will be  $Q \cdot (p - c) \cdot \Pr(V^{N:Q} \geq p)$ , while rejecting the offer generates zero profit. At the threshold the borrower is indifferent between accepting and rejecting. That is,  $Q \cdot (\tilde{p} - c) \cdot \Pr(V^{N:Q} \geq \tilde{p}) = 0$ . Then it is easy to tell that the cutoff price will be  $\tilde{p} = c$ .

Suppose now that the platform knows the borrower's true cost  $c$ . Prosper.com's profit comes from a variable fee from funded loans. We let  $\alpha$  denote the fixed percentage level. Then we can write down its expected profit as,  $E\pi_p = \alpha \cdot Q \cdot \Pr(V^{N:Q} \geq p)$ . Clearly, Prosper.com chooses a price as low as possible to maximize this profit. We can conclude that the optimal price will be

$$p^* = c. \tag{3.2}$$

### 3.3 Comparisons and hypotheses

An immediate observation is that  $p^* < r^*$ . In the current context, Prosper.com will preset an interest rate higher than what would be chosen by the borrower in the auction setting. Note also that the probability of being funded in the auctions,  $\Pr(V^{N:Q} - \lambda \geq r^*)$ , is strictly less than that with posted prices,  $\Pr(V^{N:Q} \geq p^*)$ . We therefore summarize the predictions from the model as the following:

- Prediction 1: The initial interest rates assigned by Prosper.com under the posted-price mechanism are higher than the reserve interest rates chosen by the borrowers in the auctions.
- Prediction 2: The contract interest rates in the auction stage are lower than in the posted-price stage.
- Prediction 3: The funding probability under the posted-price mechanism is higher than in the auctions.

## 4 Data and Sample

We obtained data from Prosper.com on January 14, 2013. These data cover all transactions since the website’s inception in February 2006, including both funded and failed listings. For each listing, we obtain an extensive set of variables including the requested loan amount, initial interest rate, loan term, timestamps (the starting time and ending time), and listing and loan status as of our data collection date. The borrower’s credit information includes his Prosper rating, credit score range, debt to income ratio, and many more. We also obtain detailed information at the bid level. For each bid, we observe the identity of the lender, the bidding amount of dollars and associated interest rate, the timestamp of submitting, the bid status (win or lose). For successful listings that resulted in actual loans, we have the loan origination date, contract interest rate, repayment status, and so on. For more information about the data sets and variables, please refer to our working paper version<sup>10</sup>, or see [Lin, Prabhala and Viswanathan \(2013\)](#).

In this study we focus on an empirical evaluation of the regime change. Since Prosper.com eliminated its auction model on December 20, 2010, we construct our main sample to include all listings posted between August 20, 2010 and April 19, 2011<sup>11</sup>. Table 2 and 3 in Appendix C summarizes the main sample used in our empirical analysis.

## 5 Empirical Analyses and Results

We now empirically test the predictions from our model earlier in the paper, and also explore the influence of this regime change on lenders’ bidding strategy and behaviors. We also compare the outcome of loans funded under these two market mechanisms, respectively.

---

<sup>10</sup>Available from the authors upon request.

<sup>11</sup>In some analyses later in the paper, we also utilize other samples, one of which contains all the listings posted within one year before and after the regime change date. Furthermore, prior to August 2013, Prosper.com allow borrowers to use “automatic funding” for their auctions, where the borrower sets a fixed interest rate and the auction will end as soon as 100% funding is reached. These are not included in our sample as they do not exist around the time of the regime change we study.

## 5.1 Comparisons of borrower short-term outcome

### 5.1.1 Empirical strategy

Our analytical model predicts that Prosper.com, in the posted-price stage, will assign higher interest rates compared to what the borrower would have chosen as the reserve interest rates in the auction stage (all else equal). A natural extension of that prediction is that the *contract* interest rates (for funded loans) should also be higher under posted-prices, since in auctions (with lower reserve interest rates) the final contract rate cannot be higher than the reserve rate.

We now compare these rates empirically. Notice that after the regime change, Prosper.com assigns the interest rates for borrowers according to its own categorical system, i.e. different rates for borrowers in different credit categories<sup>12</sup>. We estimate the following linear model with the interest rate category fixed effects. Specifically, let  $r_{ic}$  denote the interest rate of listing  $i$  in category  $c$ , for all the listings in our sample. We have

$$r_{ic} = \alpha_c + \beta_1 \cdot 1\{\text{Posted-Price}\}_{ic} + \gamma_1' X_{ic}^{\text{Loan}} + \gamma_2' X_{ic}^{\text{Listing}} + \gamma_3' X_{ic}^{\text{Credit}} + \varepsilon_{ic}, \quad (5.1)$$

where  $\alpha_c$  are the category fixed effects, and  $\varepsilon_{ic}$  is the idiosyncratic error term. And the  $X$ 's are the exogenous characteristics. Then the regime change effect will be reflected by the OLS (Ordinary Least Squares) estimate,  $\hat{\beta}_1$ , the coefficient for the indicator variable that equals 1 when the listing is created under pre-set interest rates (after the regime change), and 0 otherwise.

To explore the effect of regime change on the funding probability, we estimate a version of fixed effects logit model. We let  $s_{ic}$  denote a dummy variable that equals 1 if the listing  $i$  in category  $c$  is successfully funded, and 0 otherwise. Then we estimate

$$\Pr(s_{ic} = 1) = \Lambda \left( \alpha_c + \beta_1 \cdot 1\{\text{Posted-Price}\}_{ic} + \gamma_1' X_{ic}^{\text{Loan}} + \gamma_2' X_{ic}^{\text{Listing}} + \gamma_3' X_{ic}^{\text{Credit}} \right), \quad (5.2)$$

where  $\Lambda(\cdot) = \exp(\cdot)/(1 + \exp(\cdot))$  is the logit function. Again, the logit estimates of  $\beta_1$  reflects the

---

<sup>12</sup>See a screenshot of the categories on <http://web.archive.org/web/20110926231350/http://www.prosper.com/loans/rates-and-fees/>.

regime change effect on loan’s funding probabilities.

### 5.1.2 Higher funding probability? Higher interest rates?

We report the estimation results for the model (5.1) in the fourth column in both Table 5 and 6 in the Appendix D. Specifically, Table 5 reports the estimates for the comparison of *initial* interest rates. Table 6 displays the results for the comparison of final *contract* interest rates. The estimates for Model (5.2) are reported in the fourth column in Table 7. We report the marginal effects for this logit model. We also calculate the average partial effects, and the results are consistent.

The estimate for the regime change dummy in column 4 of Table 5 shows that in the posted-price sales, the initial interest rate is around 1 percent higher. Notice that if we do not incorporate the interest rate category fixed effects, the results suggest inverse direction of the comparison. For the funding probability, Table 7 shows that compared to using auctions, the funding probability using the price posting strategy is on average around 34% higher. Figure 2 also displays this apparent trend in funding probability. Notice that there is a kink at the regime change date, and this turns out to be significant even if we control for multiple covariates.

For the contract interest rates of funded loans, the fourth column in Table 6 presents a seemingly surprising result, that all else equal, the contract interest rates in the posted price stage are around 1.7 percent *lower* than in the auction stage. Our first explanation is that inexperienced borrowers create bigger variation in the initial interest rates. We observe that the average standard deviation across the interest rate categories in the auction stage is 3.894, while this value in the posted-price stage is 0.513. Another possible explanation is the funding options in the auction stage. Borrowers with urgent needs for funds tend to assign higher interest rates and use the automatic funding option. We run a simple OLS regression comparing the initial interest rates in immediate funding listings with those in other listings. Table 8 reports the estimation results. The results support our hypothesis that the initial interest rates are indeed higher in immediate funding listings<sup>13</sup>.

---

<sup>13</sup>Further details about funding options and these tests are available in the full working paper, but omitted here due to space constraints.

## 5.2 Comparisons of lender behaviors

We now turn to the effect of the regime change on lender behaviors.

### 5.2.1 Bidding behavior

Figure 4 presents the comparison of the amount of dollars submitted in each bid. It shows that in the posted-price stage, the lenders tend to invest more in each of their bids compared to that in the auction stage. Another major reason for Prosper.com to switch to the posted-price mechanism is that the funding process should be quicker. Table 4 shows that half of the funded loans from the posted price selling receive full funding within 80 hours, compared to more than 160 hours in the auction stage. In summary, after the regime change, the lenders indeed invest more and quicker on average, so that the funding procedure is indeed more efficient. Another interesting phenomenon is that in the posted-price regime, more lenders submit bids when a listing is getting closer to full funding. Figure 3 displays the distributions of bids over the final periods of listings. Compared to auctions, it is clear that under posted-price mechanism, more bids are submitted within the final hours of a listing.

### 5.2.2 Herding

Zhang and Liu (2012) studied lender herding behavior on Prosper.com. Using data from the auction stage, they find that lenders exhibit rational herding, in the sense that they gravitate toward listings with more funds received even when those listings may have seemingly “bad” credit. We adopt their empirical strategy to examine the effect of the regime change on this rational herding behavior. Specifically, we estimate the model proposed by Zhang and Liu separately using the listings posted in the auctions and in the posted-prices. Table 9 reports the estimation results. The estimates of  $\alpha_1$  express the clear difference in lenders herding behavior. In auctions, a listing with USD 100 more funding at the start of a day will receive on average USD 2.7 more funds during the day; while this number under posted prices is negative (-USD 17.2): Lenders appear to herd *away* from the listings with more existing funding.

### 5.3 Comparisons of loan outcomes

Prosper.com focuses on faster “fund deployment” as a motivation for the regime change. In the long run however, it is the repayment of the loans that matters most for investors as uncertainties resolve and returns are made. We therefore investigate how this regime change affects repayment probabilities of the loans that are funded. Since some loans originated in this period have not matured yet, for loans initiated in the auction stage, we record their repayment results as of January 14, 2013. For loans generated after the regime change, we examine their results as of May 11, 2013. This ensures that we are comparing loans at a similar stage of “maturity.” We then estimate whether the regime change is associated with a higher or lower default rates, and present the estimation results in Table 10. They suggest that, interestingly, loans after the regime change have slightly *higher* default rate, roughly 2% higher than in auctions. While somewhat surprising, this result is also reasonable: The finance literature has documented that higher interest rates on loans directly lead to higher default probabilities, and our previous results show that all else equal, Prosper.com assigns higher interest rates to loans than borrowers themselves would under auctions.

## 6 Discussions and Conclusions

In this paper we document and investigate an exogenous regime change on an online peer-to-peer lending marketplace, Prosper.com. We propose an analytical model to compare the multiunit uniform price auctions with the posted-price sales, and test its predictions using detailed transaction data from the market. Our empirical results lend support to our theoretical predictions, but also point to some interesting surprises. Specifically, we find that after the regime change, Prosper.com indeed assigns slightly higher interest rates for listings, compared to the reserve interest rates that borrowers choose in auctions. We also find significantly higher funding probability in the posted-price stage. We also offer explanations for the surprising finding that the contract interest rates under posted prices are actually lower than those in the auctions.

We further analyze the effect of the regime change on lenders’ behavior in this market. After

the regime change, lenders tend to invest more in each bid, and invest sooner, making it possible that loans can be funded faster (and therefore faster deployment of lender funds). Adopting the empirical strategy from published studies ([Zhang and Liu \(2012\)](#)), we observe an interesting *reversal* in lenders' herding behavior on the platform. Last but not least, we find that all else equal, loans funded after the regime change have slightly higher default rates than before.

These findings have important implications for researchers, practitioners, and policy-makers interested in crowd-funding, especially debt-based crowd-funding (P2P lending), both in the US and abroad. More broadly, they also contribute to the literature on electronic market design and online auctions, as well as a better understanding of how market participants' behaviors change under different market mechanisms.

## References

- Agrawal, Ajay, Christian Catalini, and Avi Goldfarb.** 2013. "The Simple Economics of Crowdfunding." In *Innovation Policy and the Economy, Volume 14*. University of Chicago Press.
- Ausubel, Lawrence M, and Peter Cramton.** 2002. "Demand Reduction and Inefficiency in Multi-Unit Auctions." *Working paper, University of Maryland*.
- Back, Kerry, and Jaime F Zender.** 1993. "Auctions of Divisible goods: On the Rationale for the Treasury Experiment." *Review of Financial Studies*, 6(4): 733–764.
- Bajari, Patrick, and Ali Hortaçsu.** 2004. "Economic Insights from Internet Auctions." *Journal of Economic Literature*, 42(2): 457–486.
- Banerjee, Abhijit V.** 1992. "A Simple Model of Herd Behavior." *Quarterly Journal of Economics*, 107(3): 797–817.
- Biais, Bruno, Peter Bossaerts, and Jean-Charles Rochet.** 2002. "An optimal IPO mechanism." *Review of Economic Studies*, 69(1): 117–146.
- Bikhchandani, Sushil, David Hirshleifer, and Ivo Welch.** 1992. "A Theory of Fads, Fashion, Custom, and Cultural Change as Informational Cascades." *Journal of Political Economy*, 992–1026.
- Bulow, Jeremy, and Paul Klemperer.** 1996. "Auctions versus Negotiations." *American Economic Review*, 86(1): 180–94.
- Casella, George, and Roger L Berger.** 2001. *Statistical Inference*. Duxbury Press.
- Economist.** 2000. "A Survey of E-commerce: in the Great Web Bazaar." *The Economist*, February 24, 2000.
- Einav, Liran, Chiara Farronato, Jonathan Levin, and Neel Sundaresan.** 2012. "Sales Mechanisms in Online Markets: What Happened to Internet Auctions?" *Working paper, Stanford University*.
- Freedman, Seth, and Ginger Zhe Jin.** 2008. "Do Social Networks Solve Information Problems for Peer-to-Peer Lending? Evidence from Prosper.com." *NET working paper*.
- Gonsalves, Atone.** 2010. "Social Lender Prosper.com Drops Auction Model." *Information Week*, December 20, 2010.
- Hammond, Robert G.** 2010. "Comparing Revenue from Auctions and Posted Prices." *International Journal of Industrial Organization*, 28(1): 1–9.
- Hammond, Robert G.** 2013. "A structural Model of Competing Sellers: Auctions and Posted Prices." *European Economic Review*, 60(1): 52–68.



- Hortacsu, Ali, and David McAdams.** 2010. "Mechanism Choice and Strategic Bidding in Divisible Good Auctions: an Empirical Analysis of the Turkish Treasury Auction Market." *Journal of Political Economy*, 118(5): 833–865.
- Krishna, Vijay.** 2009. *Auction Theory*. Academic Press.
- Kultti, Klaus.** 1999. "Equivalence of Auctions and Posted Prices." *Games and Economic behavior*, 27(1): 106–113.
- Lawton, Kevin, and Dan Marom.** 2010. *The Crowdfunding Revolution: Social Networking Meets Venture Financing*. thecrowdfundingrevolution.com.
- Lin, Mingfeng, Nagpurnanand R. Prabhala, and Siva Viswanathan.** 2013. "Judging Borrowers by the Company They Keep: Friendship Networks and Information Asymmetry in Online Peer-to-Peer Lending." *Management Science*, 59(1): 17–35.
- Lucking-Reiley, David.** 2000. "Auctions on the Internet: What are Being Auctioned, and How?" *Journal of Industrial Economics*, 48(3): 227–252.
- Simonsohn, Uri, and Dan Ariely.** 2008. "When Rational Sellers Face Nonrational Buyers: Evidence from Herding on eBay." *Management Science*, 54(9): 1624–1637.
- Wang, James JD, and Jaime F Zender.** 2002. "Auctioning Divisible Goods." *Economic Theory*, 19(4): 673–705.
- Wang, Ruqu.** 1993. "Auctions versus Posted-Price Selling." *American Economic Review*, 83(4): 838–51.
- Wilson, Robert.** 1979. "Auctions of Shares." *Quarterly Journal of Economics*, 675–689.
- Zhang, Juanjuan, and Peng Liu.** 2012. "Rational Herding in Microloan Markets." *Management Science*, 58(5): 892–912.
- Zhang, Ping.** 2009. "Uniform Price Auctions and Fixed Price Offerings in IPOs: An Experimental Comparison." *Experimental Economics*, 12(2): 202–219.

## A Derivation of Equation (3.1)

Recall that under the auction mechanism, the borrower's expected profit is

$$E\pi_A = Q \cdot \left[ E[V^{N:Q+1} - \lambda | V^{N:Q+1} - \lambda \geq r] - c \right] \cdot \Pr(V^{N:Q+1} - \lambda \geq r) \\ + Q \cdot (r - c) \cdot \Pr(V^{N:Q} - \lambda \geq r > V^{N:Q+1} - \lambda).$$

Or,

$$E\pi_A = Q \cdot E[V^{N:Q+1} | V^{N:Q+1} \geq \lambda + r] \cdot \Pr(V^{N:Q+1} \geq \lambda + r) - Q \cdot (\lambda + c) \cdot \Pr(V^{N:Q+1} \geq \lambda + r) \\ + Q \cdot (r - c) \cdot \left( \Pr(V^{N:Q} \geq \lambda + r) - \Pr(V^{N:Q+1} \geq \lambda + r) \right). \quad (\text{A.1})$$

To see that Equation (A.1) holds, note that<sup>14</sup>

$$\Pr(V^{N:Q} - \lambda \geq r > V^{N:Q+1} - \lambda) = \Pr(V^{N:Q} \geq \lambda + r > V^{N:Q+1}) \\ = \binom{N}{Q} \cdot F_V(\lambda + r)^{N-Q} \cdot (1 - F_V(\lambda + r))^Q,$$

and

$$\Pr(V^{N:Q} \geq \lambda + r) - \Pr(V^{N:Q+1} \geq \lambda + r) = (1 - G_Q(\lambda + r)) - (1 - G_{Q+1}(\lambda + r)) \\ = G_{Q+1}(\lambda + r) - G_Q(\lambda + r) \\ = \binom{N}{Q} \cdot F_V(\lambda + r)^{N-Q} \cdot (1 - F_V(\lambda + r))^Q.$$

We can rewrite Equation (A.1) as

$$E\pi_A \propto E[V^{N:Q+1} | V^{N:Q+1} \geq \lambda + r] \cdot \Pr(V^{N:Q+1} \geq \lambda + r) - (\lambda + r) \Pr(V^{N:Q+1} \geq \lambda + r) \\ - (r - c) \Pr(V^{N:Q} \geq \lambda + r), \quad (\text{A.2})$$

where we omit the constant parts. The conditional expectation in Equation (A.2) can be written as  $E[V^{N:Q+1} | V^{N:Q+1} \geq \lambda + r] = \frac{\int_{\lambda+r}^{\infty} v g_{Q+1}(v) dv}{1 - G_{Q+1}(\lambda+r)}$ . And since  $\Pr(V^{N:Q} \geq \lambda + r) = 1 - G_Q(\lambda + r)$  and  $\Pr(V^{N:Q+1} \geq \lambda + r) = 1 - G_{Q+1}(\lambda + r)$ , (A.2) can be further simplified to

$$E\pi_A \propto \int_{\lambda+r}^{\infty} v g_{Q+1}(v) dv - (\lambda + r)(1 - G_{Q+1}(\lambda + r)) \\ + (r - c)(1 - G_Q(\lambda + r)) \quad (\text{A.3})$$

<sup>14</sup>See the section of order statistics in [Casella and Berger \(2001\)](#).

The first order necessary condition to the maximization of  $E\pi_A$  is then

$$\frac{dE\pi_A}{dr} = G_{Q+1}(\lambda + r) - G_Q(\lambda + r) - (r - c)g_Q(\lambda + r) = 0$$

Then the optimal reserve price satisfies

$$r^* = c + \frac{G_{Q+1}(\lambda + r^*) - G_Q(\lambda + r^*)}{g_Q(\lambda + r^*)}. \quad (\text{A.4})$$

The second part in the RHS of (A.4) can be extended as

$$\frac{\binom{N}{Q} \cdot F_V(\lambda + r^*)^{N-Q} \cdot (1 - F_V(\lambda + r^*))^Q}{\frac{N!}{(N-Q)!Q!} \cdot f_V(\lambda + r^*) \cdot F_V(\lambda + r^*)^{N-Q} \cdot (1 - F_V(\lambda + r^*))^{Q-1}} = \frac{1 - F_V(\lambda + r^*)}{Q \cdot f_V(\lambda + r^*)}.$$

So the following holds

$$r^* = c + \frac{1 - F_V(\lambda + r^*)}{Q \cdot f_V(\lambda + r^*)}. \quad (\text{A.5})$$

(A.5) is Equation (3.1). ■

## B Policy Change

Table 1: A Comparison of Auctions versus Price Posting

	<b>Auction Stage</b>	<b>Posted-Price Stage</b>
Initial interest rate	<i>Chosen by the borrower</i>	<i>Preset by Prosper.com</i>
Funding option	<i>Automatic funding or Open-for-duration</i>	<i>Automatic funding</i>
Contract interest rate	<i>Prevailing interest rate</i>	<i>Initial interest rate</i>
Listing duration	<i>7 days</i>	<i>7 or 14 days</i>

## C Summary Statistics of the Sample

Table 2: Summary Statistics of Listing Characteristics and Credit Profiles

Variable	All Listings <sup>a</sup>		Auction Stage		Posted-Price Stage	
	Mean	sd	Mean	sd	Mean	sd
<i>Listing Characteristics</i>						
Amount Requested	6589.453	4368.212	6105.624	3953.507	7490.712	4926.057
Bids Count	70.844	93.883	58.241	94.388	94.321	88.271
Borrower Maximum Rate(%)	24.321	9.27	25.58	9.353	21.976	8.638
Borrower Rate(%)	24.098	9.232	25.237	9.34	21.976	8.638
Listing Effective Days	9.422	3.33	7.002	0.108	13.929	0.701
Dummy Listing Completed	0.342	0.474	0.227	0.419	0.554	0.497
Prosper Score	5.842	2.41	5.27	2.498	6.909	1.806
Loan Term in Months	36.737	6.11	36.201	2.789	37.737	9.533
Dummy Electronic Transfer	0.994	0.078	0.991	0.097	1	0
Dummy Description	0.998	0.046	0.998	0.042	0.997	0.053
Dummy Group Member	0.046	0.21	0.051	0.219	0.038	0.191
Dummy Images	0.159	0.365	0.243	0.429	0.002	0.047
Estimated Loss(%)	13.659	8.577	15.862	9.292	9.554	4.89
<i>Credit Profiles</i>						
Has Verified Bank Account	1	0	1	0	1	0
Is Borrower Homeowner	0.489	0.5	0.498	0.5	0.472	0.499
Amount Delinquent	1012.451	6724.713	996.725	5719.381	1041.744	8278.695
Bankcard Utilization(%)	50.527	33.926	53.121	34.564	45.695	32.154
Current CreditLines	9.063	5.29	9.075	5.306	9.041	5.261
Current Delinquencies	0.415	1.223	0.457	1.28	0.335	1.103
Inquiries Last 6 Months	1.349	1.921	1.543	2.122	0.989	1.404
Open CreditLines	7.998	4.773	7.995	4.784	8.004	4.752
Public Records Last 10 Years	0.244	0.668	0.244	0.673	0.245	0.657
Stated Monthly Income <sup>b</sup>	5010.896	13875.289	4571.001	12482.461	5830.318	16122.232
Length Credit History	5939.491	2964.225	5843.95	2915.019	6117.461	3046.116
Debt To Income Ratio (DTIR) (%)	21.287	44.724	22.073	46.132	19.824	41.943
Dummy Top Coded DTIR	0.001	0.037	0.001	0.038	0.001	0.036
Dummy Missing DTIR	0.171	0.377	0.194	0.396	0.129	0.335
Observations	13,017		8,470		4,547	

<sup>a</sup>The data sampling period in this table is between August 20, 2010 and April 19, 2011, inclusive. There is no automatic funding option in this period. The regime change occurred on December 20, 2010, after which the posted-price (pre-set interest rate) format is the only sale mechanism.

<sup>b</sup>The “Stated Monthly Income” and “Debt To Income Ratio” are reported by the borrowers, while other credit profiles are provided by Experian.

Table 3: Summary Statistics: Listing Characteristics and Credit Profiles of Funded Loans

Variable	All Loans <sup>a</sup>		Auction Stage		Posted-Price Stage	
	Mean	sd	Mean	sd	Mean	sd
<i>Listing Characteristics</i>						
Amount Requested	6102.944	4320.628	5231.256	4056.675	6774.856	4397.943
Bids Count	123.365	97.635	140.766	108.486	109.952	86.019
Borrower Maximum Rate(%)	23.307	9.25	25.418	9.475	21.679	8.732
Borrower Rate(%)	22.783	9.086	24.215	9.335	21.679	8.732
Listing Effective Days	10.915	3.476	7	0	13.933	0.68
Dummy Listing Completed	1	0	1	0	1	0
Prosper Score	6.761	1.992	6.494	2.192	6.967	1.798
Loan Term in Months	36.473	7.022	36.235	3.392	36.657	8.854
Dummy Electronic Transfer	0.998	0.045	0.995	0.068	1	0
Dummy Description	0.998	0.042	0.999	0.023	0.997	0.053
Dummy Group Member	0.056	0.231	0.072	0.259	0.044	0.206
Dummy Images	0.117	0.321	0.267	0.442	0.001	0.028
Estimated Loss(%)	10.372	6.111	11.608	7.254	9.419	4.847
<i>Credit Profiles</i>						
Has Verified Bank Account	1	0	1	0	1	0
Is Borrower Homeowner	0.511	0.5	0.525	0.5	0.501	0.5
Amount Delinquent	772.968	6043.113	680.416	4331.649	844.31	7085.693
Bankcard Utilization(%)	50.723	32.594	52.822	33.074	49.106	32.132
Current Credit Lines	9.24	5.182	9.202	5.12	9.268	5.23
Current Delinquencies	0.341	1.141	0.36	1.174	0.326	1.115
Inquiries Last 6 Months	0.938	1.377	0.98	1.468	0.905	1.302
Open CreditLines	8.153	4.672	8.103	4.638	8.192	4.699
Public Records Last 10 Years	0.261	0.653	0.256	0.635	0.265	0.667
Stated Monthly Income <sup>b</sup>	5532.575	12427.715	5043.268	4095.139	5909.741	16133.642
Length Credit History	5994.125	2819.694	5936.948	2838.113	6038.199	2805.183
Debt To Income Ratio (DTIR)(%)	19.768	33.415	19.674	31.181	19.841	35.046
Dummy Top Coded DTIR	0.001	0.026	0.001	0.023	0.001	0.028
Dummy Missing DTIR	0.103	0.304	0.111	0.314	0.097	0.296
Observations	4466		1944		2522	

<sup>a</sup>This table presents the summary statistics of the corresponding variables from the funded loans. The data sampling period in this table is between August 20, 2010 and April 19, 2011, inclusive. Prosper.com no longer allowed “automatic funding” in this period. The regime change occurred on December 20, 2010, after which posted-price (pre-set interest rate) format is the only sales mechanism.

<sup>b</sup>The “Stated Monthly Income” and “Debt To Income Ratio” are reported by the borrowers, while other credit profiles are provided by Experian.

Figure 1: Daily Average Interest Rate of Funded Loans before and after the Regime Change

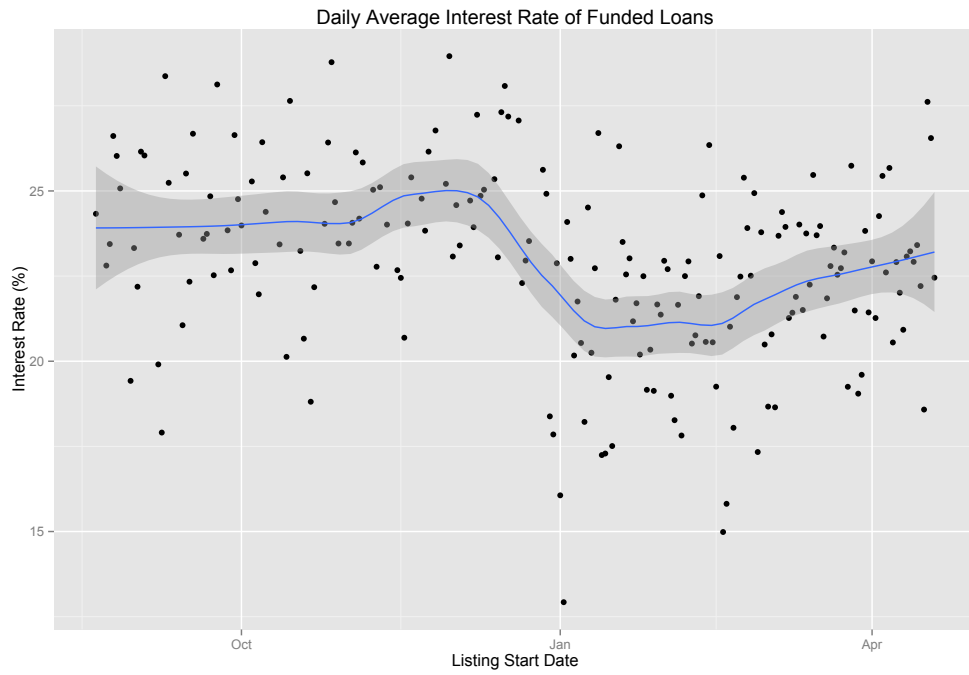


Figure 2: Daily Percentage of Funded Loans before and after the Regime Change

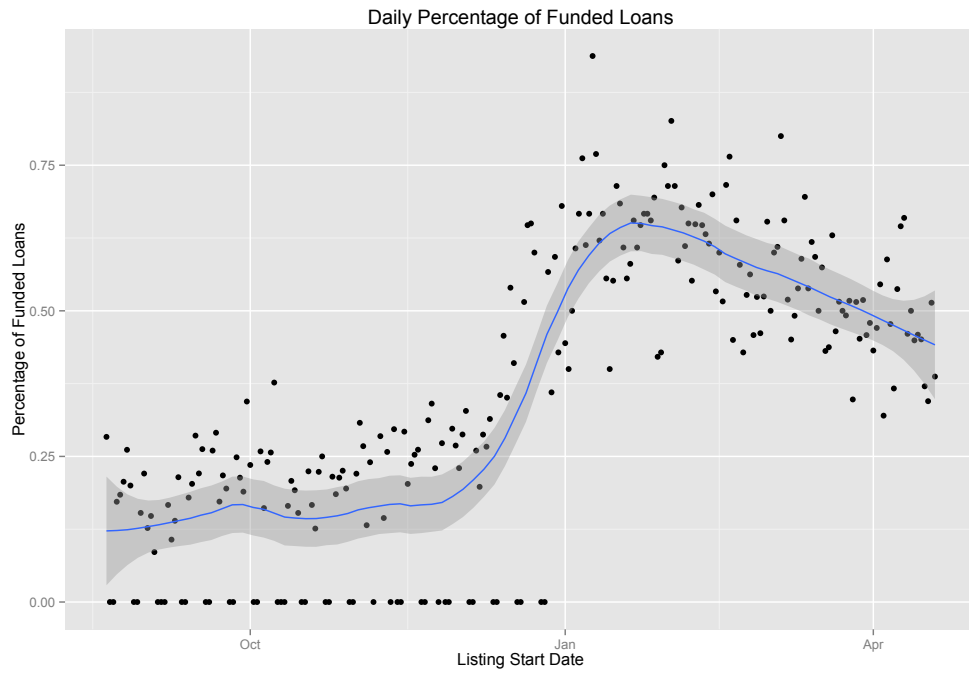


Figure 3: The Timing of Lender Investments before and after the Regime Change

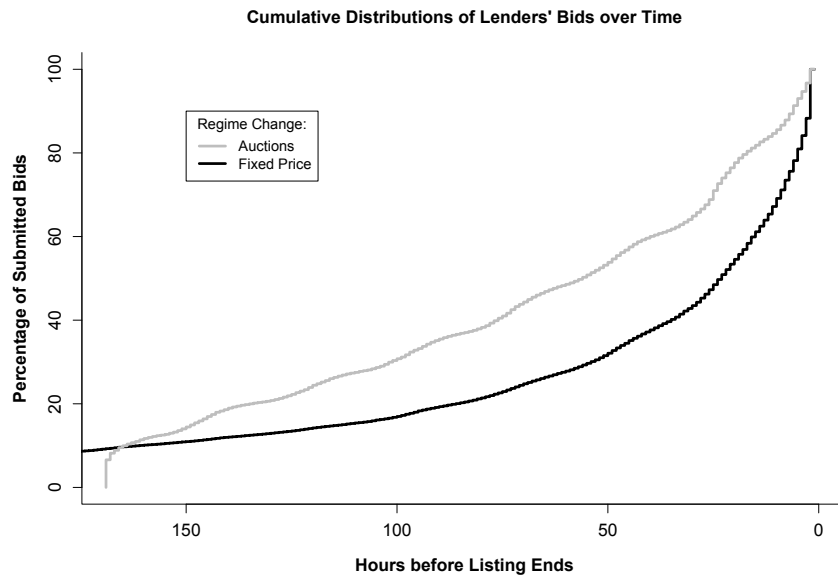


Figure 4: Distribution of Invest Amount per Bid before and after the Regime Change

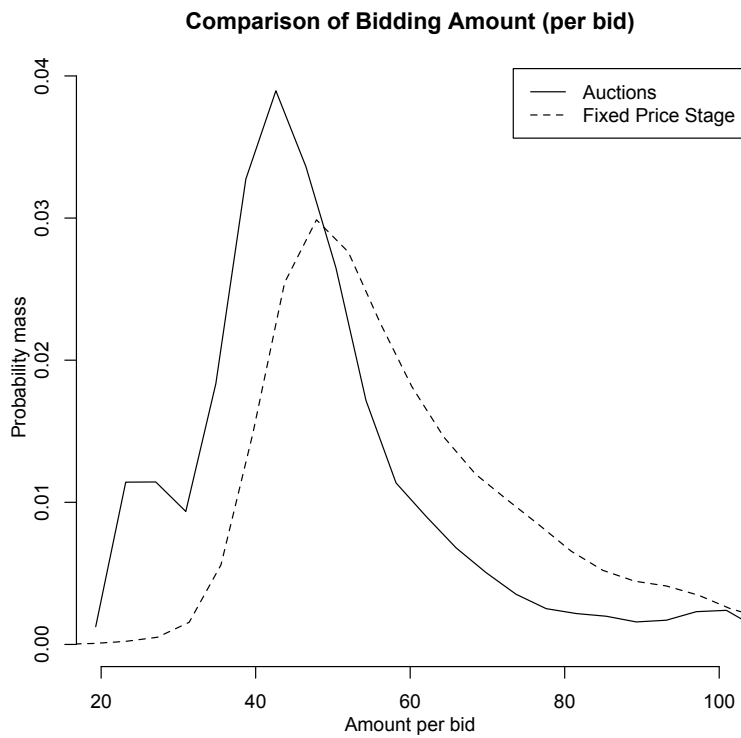




Table 4: Hours before Receiving Full Funding

<b>Statistics</b>	<b>Auctions</b>	<b>Posted-Price</b>
	Effective Time (hrs)	Effective Time (hrs)
Median	164.40	80.26
Mean	132.70	127.80
SD	48.49	119.95
Minimum	0.19	0.02
Maximum	169.10	336.20
Num. obs.	1944	2522
Typical Duration (in days)	7	14

## D Estimation Results

Table 5: Results for the Borrowers' Maximum Interest Rates

Dep var.: Borrower's Maximum Interest Rate	OLS Results			
	Spec 1	Spec 2	Spec 3	Spec 4
<b>Dummy Posted-Price (<math>\beta_1</math>)</b>	-3.604*** (0.167)	-2.081*** (0.159)	-1.494*** (0.153)	1.063*** (0.104)
Amount Requested		-0.001*** (0.000)	-0.001*** (0.000)	0.000*** (0.000)
Debt To Income Ratio (DTIR)		0.055*** (0.003)	0.067*** (0.003)	0.002 (0.002)
Dummy Missing DTIR		4.568*** (0.205)	5.204*** (0.197)	-0.009 (0.130)
Dummy Top Coded DTIR		-55.516*** (3.461)	-67.655*** (3.341)	-4.976** (2.142)
Is Borrower Homeowner		-0.927*** (0.161)	-0.811*** (0.162)	-0.115 (0.102)
DTIR * Homeowner		0.012*** (0.003)	0.012*** (0.003)	0.005*** (0.002)
Dummy Electronic Transfer		-3.346*** (0.908)	-2.587*** (0.867)	-1.457*** (0.543)
Dummy Description		1.315 (1.530)	1.669 (1.458)	0.080 (0.913)
Dummy Group Member		0.778** (0.340)	0.483 (0.325)	0.504** (0.210)
Dummy Images		-0.385* (0.206)	-0.150 (0.196)	0.222* (0.124)
Current Delinquencies			0.658*** (0.061)	0.069* (0.039)
Delinquencies Last 7 Years			0.113*** (0.009)	0.027*** (0.006)
Length Credit History			0.000*** (0.000)	0.000*** (0.000)
Total Credit Lines			-0.015*** (0.006)	-0.019*** (0.004)
Public Records Last 10 Years			0.936*** (0.105)	0.347*** (0.066)
Inquiries Last 6 Months			0.961*** (0.036)	0.043* (0.024)
(Intercept)	25.580*** (0.099)	30.943*** (1.783)	27.125*** (1.709)	
<b>IR Category FE</b>	No	No	No	Yes
Adj. R <sup>2</sup>	0.034	0.240	0.310	0.966
Num. obs.	13017	13017	13017	13017

\*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$

Table 6: Results for the Contract Interest Rates

Dep var.: Borrower Rate	OLS Results				
	Spec 1	Spec 2	Spec 3	Spec 4	Spec 5
<b>Dummy Posted-Price (<math>\beta_1</math>)</b>	-2.537*** (0.272)	-3.923*** (0.282)	-3.831*** (0.269)	-1.749*** (0.081)	-0.473*** (0.071)
Amount Requested		0.000 (0.000)	0.000 (0.000)	0.000*** (0.000)	0.000*** (0.000)
Bid Count		-0.047*** (0.002)	-0.042*** (0.002)	-0.007*** (0.001)	-0.010*** (0.001)
Debt To Income Ratio (DTIR)		0.074*** (0.006)	0.091*** (0.006)	0.000 (0.002)	-0.001 (0.001)
Dummy Missing DTIR		5.011*** (0.394)	6.224*** (0.379)	-0.288* (0.114)	-0.300** (0.094)
Dummy Top Coded DTIR		-71.309*** (6.866)	-87.699*** (6.648)	1.261 (1.978)	1.993 (1.618)
Is Borrower Homeowner		-1.408*** (0.271)	-1.448*** (0.269)	-0.022 (0.078)	-0.068 (0.064)
DTIR * Homeowner		0.013 (0.007)	0.016* (0.007)	-0.004* (0.002)	-0.003* (0.002)
Listing Effective Days		0.226*** (0.030)	0.150*** (0.029)	-0.136*** (0.009)	-0.076*** (0.007)
Dummy Electronic Transfer		-2.747 (2.496)	-2.558 (2.376)	-1.259 (0.689)	-1.005 (0.564)
Dummy Description		2.668 (2.645)	2.440 (2.518)	0.002 (0.734)	-0.019 (0.600)
Dummy Group Member		-0.498 (0.488)	-0.863 (0.466)	-0.351* (0.141)	-0.444*** (0.115)
Dummy Images		-0.309 (0.385)	-0.476 (0.367)	-0.246* (0.107)	-0.321*** (0.087)
Current Delinquencies			0.762*** (0.102)	0.116*** (0.030)	0.070** (0.024)
Delinquencies Last 7 Years			0.104*** (0.016)	0.014** (0.005)	0.010** (0.004)
Length Credit History			0.000* (0.000)	0.000 (0.000)	0.000 (0.000)
Total Credit Lines			0.010 (0.009)	0.002 (0.003)	0.001 (0.002)
Public Records Last 10 Years			0.750*** (0.171)	0.020 (0.050)	0.008 (0.041)
Inquiries Last 6 Months			1.275*** (0.079)	-0.036 (0.024)	-0.039* (0.020)
Borrower Maximum Rate					0.662*** (0.014)
(Intercept)	24.215*** (0.204)	28.351*** (3.638)	25.816*** (3.471)		
<b>IR Category FE</b>	No	No	No	Yes	Yes
Adj. R <sup>2</sup>	0.019	0.325	0.389	0.993	0.995
Num. obs.	4466	4466	4466	4466	4466

\*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$

Table 7: Results for the Funding Probability

Dep var.: Borrower Rate	Logit Results (Marginal Effects) <sup>a</sup>				
	Spec 1	Spec 2	Spec 3	Spec 4	Spec 5
<b>Dummy Posted-Price (<math>\beta_1</math>)</b>	0.327*** (0.009)	0.351*** (0.010)	0.344*** (0.010)	0.338*** (0.020)	0.332*** (0.021)
Amount Requested		0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)
Bid Count		0.004*** (0.000)	0.004*** (0.000)	0.003*** (0.000)	0.003*** (0.000)
Debt To Income Ratio (DTIR)		0.000 (0.000)	-0.001*** (0.000)	0.000** (0.000)	0.000** (0.000)
Dummy Missing DTIR		-0.088*** (0.010)	-0.097*** (0.010)	-0.076*** (0.012)	-0.070*** (0.011)
Dummy Top Coded DTIR		-0.059 (0.171)	0.414 (0.307)	0.445 (0.326)	0.520* (0.308)
Is Borrower Homeowner		0.045*** (0.010)	0.034*** (0.010)	0.038*** (0.010)	0.034*** (0.009)
DTIR * Homeowner		0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Listing Effective Days		-0.003** (0.001)	-0.001 (0.001)	0.003** (0.001)	0.005*** (0.001)
Dummy Electronic Transfer		0.200*** (0.070)	0.193*** (0.070)	0.139** (0.067)	0.151** (0.061)
Dummy Description		-0.011 (0.093)	-0.004 (0.097)	0.003 (0.095)	-0.007 (0.087)
Dummy Group Member		0.103*** (0.024)	0.097*** (0.024)	0.002 (0.020)	-0.002 (0.018)
Dummy Images		0.012 (0.013)	0.008 (0.013)	-0.011 (0.013)	-0.013 (0.011)
Current Delinquencies			-0.013*** (0.004)	-0.011*** (0.004)	-0.011*** (0.004)
Delinquencies Last 7 Years			-0.001* (0.001)	-0.001 (0.001)	-0.001** (0.000)
Length Credit History			0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)
Total Credit Lines			0.002*** (0.000)	0.002*** (0.000)	0.002*** (0.000)
Public Records Last 10 Years			0.021*** (0.006)	0.019*** (0.006)	0.014** (0.006)
Inquiries Last 6 Months			-0.027*** (0.003)	-0.020*** (0.003)	-0.018*** (0.003)
Borrower Maximum Rate					0.023*** (0.002)
<b>IR Category FE</b>	No	No	No	Yes	Yes
Num. obs.	13017	13017	13017	13017	13017

\*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$

<sup>a</sup>The marginal effects are reported in this table.

Table 8: Immediate Funding Comparisons

Dep var.: Borrower Maximum Rate	OLS results	
	Spec 1 <sup>a</sup>	Spec 2
<b>Dummy Immediate Funding<sup>b</sup></b>	2.048*** (0.305)	1.989*** (0.305)
Amount Requested	0.000*** (0.000)	0.000*** (0.000)
Debt To Income Ratio (DTIR)	0.030*** (0.002)	0.029*** (0.002)
Dummy Missing DTIR	2.916*** (0.139)	2.918*** (0.139)
Dummy Top Coded DTIR	-29.702*** (2.282)	-28.631*** (2.282)
Is Borrower Homeowner	-1.644*** (0.124)	-1.790*** (0.125)
Duration	-1.927*** (0.507)	-1.848*** (0.505)
Dummy Electronic Transfer	1.405*** (0.525)	1.216** (0.524)
Dummy Description	0.915 (1.469)	0.917 (1.466)
Dummy Group Member	1.119*** (0.218)	1.140*** (0.219)
Dummy Images	-0.139 (0.113)	-0.124 (0.114)
Current Delinquencies	1.000*** (0.047)	0.991*** (0.047)
Delinquencies Last 7 Years	0.128*** (0.007)	0.127*** (0.007)
Total Credit Lines	-0.029*** (0.004)	-0.031*** (0.004)
Public Records Last 10 Years	1.346*** (0.084)	1.265*** (0.084)
Inquiries Last 6 Months	0.981*** (0.025)	1.018*** (0.025)
Length Credit History	0.000*** (0.000)	0.000*** (0.000)
DTIR * Is Borrower Homeowner	0.004* (0.002)	0.004 (0.002)
(Intercept)	37.039*** (3.843)	
Borrower State FE	No	Yes
Adj. R <sup>2</sup>	0.189	0.891
Num. obs.	28973	28973

\*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$

<sup>a</sup>Note that the sample listings used in this set of regressions were posted between December 20, 2009 and December 19, 2010, inclusive.

<sup>b</sup>It equals 1 if the listing specifies the funding option as “close when funded”, otherwise it is 0.

## E Lenders' Herding Behavior and Loan Payment Results

Table 9: Results for the Funding Probability

Dep var.: Daily fund received	Within Estimates	
	Auctions	Posted-Price
Lag Cum Amount( $\alpha_1$ )	0.027* (0.014)	-0.172*** (0.018)
Lag Percent Needed	-0.005*** (0.000)	-0.003*** (0.001)
Lag Min Rate	-0.098*** (0.022)	
Lag Bids	-0.001 (0.001)	0.015*** (0.001)
Lag Cum Amount * Lag Percent Needed	0.001*** (0.000)	0.008*** (0.000)
Listing FE	Yes	Yes
Day of Listing FE	Yes	Yes
Weekday of Listing	Yes	Yes
Adj. R <sup>2</sup>	0.090	0.252
Num. obs. <sup>a</sup>	24773	21366

\*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$

<sup>a</sup>Note that the listings sampled in this table include only those with at least one bid.

Table 10: Loan Repayment Results

Dep var.: 1(Loan Defaulted)	Marginal Effects <sup>a</sup>			
	Spec 1	Spec 2	Spec 3	Spec 4
<b>Dummy Posted-Price</b>	0.023** (0.011)	0.025** (0.010)	0.021** (0.009)	0.023** (0.009)
Amount Requested		0.000** (0.000)	0.000*** (0.000)	0.000*** (0.000)
Borrower Rate		0.022*** (0.004)	0.023*** (0.004)	0.041*** (0.011)
Borrower Rate <sup>2</sup>		0.000*** (0.000)	0.000*** (0.000)	-0.001*** (0.000)
Debt To Income Ratio (DTIR)		0.000*** (0.000)	0.000 (0.000)	0.000 (0.000)
Dummy Missing DTIR		0.002 (0.015)	0.011 (0.015)	0.012 (0.015)
Dummy Top Coded DTIR		0.030 (0.312)	-0.090*** (0.032)	-0.090*** (0.026)
Is Borrower Homeowner		-0.038*** (0.011)	-0.007 (0.012)	-0.008 (0.012)
DTIR*Homeowner		0.000 (0.000)	0.000 (0.000)	0.000* (0.000)
Amount Delinquent			0.000 (0.000)	0.000 (0.000)
Bankcard Utilization			0.000*** (0.000)	0.000** (0.000)
Current Credit Lines			0.002 (0.003)	0.002 (0.003)
Current Delinquencies			0.012*** (0.004)	0.012*** (0.003)
Delinquencies Last 7 Years			-0.001* (0.001)	-0.001* (0.001)
Income			-0.013*** (0.004)	-0.012*** (0.004)
Inquiries Last 6 Months			0.014*** (0.003)	0.014*** (0.003)
Open Credit Lines			-0.008* (0.004)	-0.007* (0.004)
Public Records Last 10 Years			-0.006 (0.007)	-0.006 (0.007)
Public Records Last 12 Months			0.009 (0.035)	0.009 (0.035)
Revolving Credit Balance			0.000 (0.000)	0.000 (0.000)
Total Credit Lines			-0.001** (0.000)	-0.001** (0.000)
Total Open Revolving Accounts			0.004 (0.003)	0.003 (0.003)
Length Credit History			0.000*** (0.000)	0.000*** (0.000)
(Intercept)	-0.229*** (0.006)	-0.560*** (0.044)	-0.495*** (0.045)	
<b>Prosper Rating FE</b>	No	No	No	Yes
Num. obs. <sup>b</sup>	4082	4082	4082	4082

\*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$

<sup>a</sup>The marginal effects from the logit regressions are reported.

<sup>b</sup>In this set of logit regressions we focus on loans with 36-month maturity, dropping a small set of loans due in 12 or 60 months.