Center for Analytical Finance
University of California, Santa Cruz

Working Paper No. 19

Market Mechanisms in Online Crowdfunding

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July 2015

Abstract

Online crowdfunding has emerged as an appealing new channel of financing in recent years. A fundamental but largely unanswered question in this nascent industry is the choice of market mechanisms, i.e., how the supply and demand of funds are matched, and the terms (price) at which transactions will occur. Two of the most popular such mechanisms are auctions (where the \crowd" determines the price of the transaction through an auction process) and posted prices (where the platform determines the price). While crowdfunding platforms typically use one or the other, there is little systematic research on the implications of such choices for the behavior of market participants, transaction outcomes, and social welfare. We address this question both theoretically and empirically in the context of debt-based crowdfunding. We first develop a game-theoretic model that yields empirically testable hypotheses, taking into account the incentive of the crowdfunding platform. We then test these hypotheses by exploiting a regime change from auctions to posted prices on one of the largest debt-based crowdfunding platforms. Consistent with our hypotheses, we find that under platform-mandated posted prices, loans are funded with higher probability, but the pre-set interest rates are higher than borrowers' starting interest rates in auctions. More important, all else equal, loans funded under the posted-price regime are more likely to default, thereby undermining lenders' returns on investment and their surplus from trading. Although platform-mandated posted prices may be faster in originating loans, auctions that rely on the "crowd" to discover prices are not necessarily inferior in terms of overall social welfare.

Key words: Crowdfunding, Peer-to-peer lending, Market mechanisms, Auctions, Posted prices

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Seed funding for CAFIN has been provided by Dean Sheldon Kamieniecki of the Division of Social Sciences at the University of California, Santa Cruz.

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* The authors contribute equally in this research. We thank Gongpil Choi, Keisuke Hirano, Tanjim Hossain, Christopher Lamoureux, Adair Morse, Chris Parker, Jeffrey Prince, Stanley Reynolds, Siva Viswanathan, John Wooders, Mo Xiao, and seminar participants at the University of Arizona, Purdue University, the 2013 Conference on Information Systems and Technology, the 2013 Workshop on Information Systems and Economics, the 12th International Industrial Organization Conference, the Conference on Internet Search and Innovation at Northwestern University, the Academic Symposium on Crowdfunding at the University of California, Berkeley, and the Platform Strategy Research Symposium at Boston University for helpful comments and suggestions. All errors remain our own.

1. Introduction

In recent years, online crowdfunding has emerged as an appealing new channel of financing (Agrawal et al. 2013, Burtch et al. 2013, Lin et al. 2013, Lin and Viswanathan 2015). It is broadly defined as the aggregation of funds from individuals or organizations to support another person or organization via the Internet. Based on what the funds are in exchange for, crowdfunding can be broadly classified as debt-, rewards-, equity-, or donation-based. All types of crowdfunding have received enormous interest and experienced tremendous growth in the past few years, worldwide. By one estimate, in the year 2014 alone in the United States, debt-based crowdfunding (also known as peer-to-peer lending) generated more than $8.9 billion in loans, and received more than $1.32 billion in venture capital investments.[1] Reward-based crowdfunding sites such as Kickstarter have grown exponentially in the past few years; donation-based crowdfunding sites as Kiva connect investors in developed countries to developing regions of the world; and equity-based crowdfunding, despite some initial legal difficulties, has gradually expanded in the US thanks to the 2012 JOBS Act.[2]

Regardless of the type, online crowdfunding platforms are essentially *markets* that match supply and demand of funds. A fundamental question in any market—be it online or offline, for physical products or financial products—is how to match demand and supply and uncover the "correct" price for transactions to occur; namely, what the market mechanism should be. Two of the most common market mechanisms, both of which have seen implementations in crowdfunding, are auctions and posted prices. As their names suggest, auctions typically rely on the relative strength of the market participants (*i.e.*, supply vs. demand) to uncover the price, through an auction process; posted prices start with a pre-determined price instead. Online crowdfunding platforms mostly choose one or the other, and this important choice lays the foundations for investors and fundraisers to "match" with each other in these markets. It has the potential to affect the behavior of both sides of the market, the platform, and overall social welfare, and is therefore an important research topic (Wang 1993, Biais et al. 2002, Hortaçsu and McAdams 2010). However, there is little systematic research on the comparison of these mechanisms in the context of crowdfunding, despite its potential impact on this nascent but burgeoning industry. The research question that we address in this paper, therefore, is: *How do these mechanisms compare in terms of their influence on market participant behaviors, transaction outcomes, and social welfare?*

We focus on debt-based crowdfunding to address this research question rather than other types of crowdfunding for several reasons. First, debt-based crowdfunding formally recognizes and uses

[1] http://cdn.crowdfundinsider.com/wp-content/uploads/2015/04/P2P-Lending-Infographic-RealtyShares-2014.jpg

[2] The JOBS Act amends Section 4 of the Securities Act to exempt security issuers from some requirements when they offer and sell up to $1 million in securities, provided that individual investments do not exceed certain thresholds and other conditions are satisfied. One condition is that issuers can use a crowdfunding intermediary. More information on the Securities and Exchange Commission (SEC) website: `http://www.sec.gov/spotlight/jobs-act.shtml`.

both types of market mechanisms. Second, it has an unequivocal and universal metric for "price," *i.e.*, interest rate of loans. Third, the *ex post* resolution of uncertainty associated with each loan can be objectively measured when loans reach their maturity. Comparing the impact of market mechanisms is therefore much more natural in debt crowdfunding than other types of crowdfunding. In addition, we observe a unique regime change on a debt-based crowdfunding platform.

We first propose an analytical model comparing the multiunit uniform price auctions against the posted-price mechanism in the context of debt crowdfunding. Our model predicts that the crowdfunding platform, the pricing agent in the posted-price regime, will assign *higher* interest rates compared to what the borrowers would have chosen as their reserve interest rates in auctions. Meanwhile, loans will be funded with *higher* probability under the posted-price mechanism. By natural extension, the contract interest rates for loans funded in the posted-price regime will be *higher* as well, since in auctions the final interest rates cannot be higher than borrowers' reservation interest rates. Further, since loans with higher interest rates are more likely to default (all else equal) (Stiglitz and Weiss 1981, Bester 1985), loans funded under posted prices should be *more* likely to default as well.

To test these predictions, our empirical analysis employs detailed transactions data from Prosper.com, one of the leading debt-based crowdfunding platforms in the US. Prosper.com is an online market for unsecured personal loans. Since its inception in 2005, Prosper.com had used auctions as its market mechanism, and because of that it was aptly called the "eBay for personal loans." But on December 20, 2010, Prosper.com unexpectedly abandoned its well-known auction model and switched the entire website to a posted-price mechanism (Renton 2010).[3] This regime change was effective immediately on the whole site, and unanticipated by market participants. It therefore provides an ideal opportunity to investigate how different market mechanisms impact participant behaviors and market efficiency, especially considering the incentives of the platform itself.[4] More specifically we focus on listings initiated during a short time period before and after the regime change, from August 20, 2010 to April 19, 2011. We compare the pricing (the initial interest rate of a listing), funding probabilities (the listings' probability of full funding), the contract interest rates, as well as default probabilities of funded loans. Consistent with our theoretical predictions,

[3] Renton (2010) provides evidence that this change was largely unexpected. 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/`. In addition to the change in market mechanism Prosper.com also changed the standard duration of auctions. We rule out the duration change as an alternative explanation to our findings later in the paper; see 6.1.2.

[4] As is common in the literature, data generated from such natural experiments provides clean identification opportunities in a natural setting; its strength lies in the internal validity. Meanwhile for our study, even though this was an exogenous event, the website today (as of the time of writing) is not dramatically from what it was in 2010. In addition, our analysis is based on our hypotheses developed from a game theoretic model that captures incentive structures of all stakeholders; and these incentives are still the same today. The use of data from this natural experiment, therefore, does not diminish the general relevance and applicability of our findings.

under posted prices, listings are much more likely to be funded and they are also funded faster. These results are consistent with our analyses of lender behavior after the regime change: they submit larger bids and submit their bids sooner, and rely less on the actions of other lenders (less herding). In addition, we find that the initial and contract interest rates under the posted-price mechanism are both higher than those in auctions. In other words, while the regime change indeed led to a higher funding probability, it came at a cost of higher interest rates. More important, we find evidence that loans funded under the posted-price regime are more likely to default, and the hazard rate of default is *higher* for loans initiated after the regime change. These long-term results have important implications, but have not been previously documented.

We further examine the welfare implications of the regime change. We first show analytically that under certain conditions, social welfare can in fact be higher under auctions than posted prices. In particular, the increase in platform profits (fees from higher probability of successful funding) is no greater than the decrease in borrower surplus. For the total surplus, the ambiguity lies with lender surplus since the contract interest rate and default rate both increase. To ascertain the change in lender surplus, we first calculate lenders' return-on-investment on loans originated, then further numerically calibrate lender's supply curve so as to derive lender surplus (*cf.* producer surplus). Comparisons of these results across market mechanisms show that lender surplus is strictly lower under posted prices. Hence, the total social welfare is in fact *lower* after the regime change.

Our study is among the first to compare two popular market mechanisms both theoretically and empirically to understand their impact on participant behaviors, transaction outcomes, and social welfare. Our paper therefore contributes to the growing literature on crowdfunding in general, and the research on peer-to-peer lending in particular. Recent investigations include Burtch et al. (2013), Hahn and Lee (2013), Iyer et al. (2010), Kawai et al. (2014), Kim and Hann (2014), Lin et al. (2013), Lin and Viswanathan (2015), Rigbi (2013), and Zhang and Liu (2012). Given the global expansion of crowdfunding our study has important and timely implications not only for researchers and practitioners, but for policymakers as well. Since crowdfunding is essentially sourcing *funds* from the crowd, our study also contributes to the growing literature on crowdsourcing, such as Chen et al. (2014a), Dellarocas et al. (2010), Hosanagar et al. (2010), and Liu et al. (2014). Furthermore, our work also contributes to a long literature on the optimal sales mechanism, and auctions in particular. For instance, Bulow and Klemperer (1996) compare auctions against negotiations, whereas Wang (1993) provides theoretical comparison between single object auctions and posted-price mechanisms. More recent comparisons of these market mechanisms, particularly between posted prices and auctions, can be found in such diverse fields as treasury auctions (Ausubel and Cramton 2002, Hortaçsu and McAdams 2010), initial public offerings (IPO) (Biais et al. 2002, Zhang 2009), and online product markets (Chen et al. 2014b) such as eBay.com (Wang et al. 2008, Einav et al. 2013, Hammond 2010, 2013).

2. Research Context

Since the inception of Zopa.com in 2005 in the United Kingdom, debt-based crowdfunding, or online peer-to-peer 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. By the end of 2014, there had been over 2 million registered members (either as a borrower, a lender, or both) on Prosper.com. More than $100,000$ unsecured personal loans, valued over USD 2.4 billion in total, have been funded.

A brief outline of the funding process on Prosper.com is as follows.[5] A potential borrower first registers on Prosper.com and verifies identity. After that, the borrower creates a listing web page, describing the purpose, requested amount, and duration of the loan (typically 3 years). The request also specifies the initial interest rate, which has different meanings under different market mechanisms. Before December 20, 2010, under auctions, this is the borrower's reservation or maximum interest rate that they are willing to accept. After the regime change, Prosper.com *presets* an interest rate for the loan based on the borrower's creditworthiness.

Prior to the regime change on December 20, 2010, once the listing is posted with a specified duration (typically 7 days), 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 auction. In their bids, lenders specify the amount of funds that they would like to invest, and the *minimum* interest rate at which they are willing to lend. Typically many lenders fund a loan together. All lenders can observe previous lenders' identities and their bidding amount. Lender's priority in participating in the loan is ranked by the interest rate that they specified in their bids, where those with lowest interest rates are most likely to participate. During the auction, the ongoing interest rate is either the starting interest rate that the borrower sets at the beginning, if the loan is not 100%funded; or the lowest interest rate among all lenders that are outbid (excluded from funding the loan) once funds from lenders exceed the requested amount. At the end, if the loan receives full funding, the winners will be all lenders who specified the lowest interest rates among all those who bid; the contract interest rate will be the ongoing interest rate at the end. In other words, the borrower sets the initial interest rate and the auction helps "discover" the contract interest rate.

On December 20, 2010, Prosper.com unexpectedly eliminated this auctions model. Since then, the interest rate is preset by Prosper.com based on the website's evaluation of the borrower's creditworthiness. The borrower can no longer use the auction format. Lenders now only specify a

[5] Our descriptions are accurate for the period of time that we study. We emphasize website features that are most relevant to our investigation, but may not cover all institutional details. Interested readers can refer to other studies using data from Prosper.com such as Zhang and Liu (2012), Lin et al. (2013), Freedman and Jin (2011) and Lin and Viswanathan (2015) for further details.

dollar amount for their investment, implicitly accepting the preset interest rate. Multiple lenders are still allowed to fund a loan. Listings will not be converted into loans unless the full amount requested by the borrower is funded before listing expiration; and the contract interest rate is the rate preset at the beginning. Table 1 summarizes the key difference between these two regimes.

Table 1 A Comparison of Auctions vs. Price Posting—The Regime Change

	Auction Regime	Posted-Price Regime
Initial interest rate	*Chosen by the borrower*	*Preset by Prosper.com*
Contract interest rate	*Prevailing interest rate at the end of auction*	*Initial interest rate*

When announcing the regime change, Prosper.com argued that the new market mechanism would allow "*…a quicker deployment of funds*" for investors, and borrowers would "*get their loan listing funded sooner*." "Quicker deployment" refers to the fact that investors' funds can only generate returns when invested in a loan that is successfully funded. To understand whether the regime change indeed had these effects, and more important whether there are other consequences of this change, we develop a stylized model to generate several empirically testable hypotheses. We then test the model's predictions using data from Prosper.com around the time of regime change.

Before we dive into the analytical model, it is also worth noting that intuitions behind our hypotheses are straightforward and will be described in detail. The model in the next section provides a more general and formal treatment of the hypothesis derivation.

3. A Model of Market Mechanisms

We now propose a model to compare the multiunit uniform price auctions against platform-mandated posted prices in the context of Prosper.com. The benefit of the game theoretic model is that it not only captures primary features of the two market mechanisms, but also mathematically models the incentive of key stakeholders including borrowers, lenders, and the platform. It allows a more formal process of hypothesis development. More important, the analytical model ensures that our hypotheses are based on general features of the market and stakeholder incentives, not peculiarities of the natural experiment that we later exploit for empirical testing. For these reasons, this approach (using analytical models to derive hypotheses then empirically test them) has been used in many empirical studies in information systems and economics, such as Arora et al. (2010), Lemmon and Ni (2014), and Sun (2012).

Our 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). We develop the following model to highlight the key difference between auctions and the posted-price mechanisms (Chen et al. 2014c). Consider a borrower requesting a personal loan on the platform. In an auction, either the lowest losing interest rate or the borrower's initial interest rate sets the contract interest rate for all winning lenders if the loan is funded. Under posted prices, Prosper.com presets the interest rate for the loan, and the borrower either accepts or rejects it. Once the borrower accepts and the listing is created, any lender can "purchase" a portion of the loan at the pre-set interest rate. All lenders will fund the personal loan at this rate. We denote p as the contract rate of a loan funded from either an auction or a posted-price sale. A highly consistent finding in the finance literature (Stiglitz and Weiss 1981, Bester 1985) is that higher contract interest rates cause higher default rates. Hence, let $\delta(p)$ be the default rate given the contract interest rate is p, where $\delta^{'}(\cdot) \geq 0$.

For the borrower, there is a variable cost c for each dollar he or she borrows from the site. If the loan is successfully funded, this cost (*cf.* Prosper.com fees) will be deducted before the borrower receives the funds. The borrower may also incur other explicit or implicit costs, such as their time and efforts in creating the request. For simplicity, we assume that the borrower is requesting a loan with Q units, and the discount rate is τ. This can be interpreted as the lowest interest rate from his or her outside options or other channels. The maximum interest rate that the borrower is willing to pay for this loan on Prosper.com will then be $\tau - c$.

On the other side of the market, suppose there are N potential lenders for this particular loan. We assume $N \gg Q$, *i.e.*, there are always enough lenders to fund the loan if the price is right. This assumption is reasonable considering the large pool of lenders on Prosper.com. We assume that each lender supplies at most one unit of the loan, and has an independent private willingness to lend (WTL). A lender's WTL is the lowest rate at which they are willing to lend the borrower. They will never fund the listing at any interest rate below this WTL. This is equivalent to the lender's true valuation of the loan, or the maximum risk-free interest rate from the lender's outside options. The private value assumption is not restrictive given the fact that there were no resale opportunities for loans during the time we study, so a lender's WTL is independent of others' valuations. Let W_n denote lender n's WTL, $n = 1, 2, ..., N$. Let w_n denote its realization. We assume that W_n is IID (independent and identically distributed) with CDF $F_W(\cdot)$, and PDF $f_W(\cdot)$. We let $W^{N:k}$ denote the k-th lowest value among N IID willingness-to-lend, and $k = 1, 2, ..., N$. Let $w^{N:k}$ denote its realization. We denote the distribution of $W^{N:k}$ by $G_k(\cdot)$ (or PDF $g_k(\cdot)$).

3.1. Auctions

We model a multiunit uniform price auction with single-unit demand. In such an auction, the market clearing interest rate is set by the lowest losing bid or the borrower's reserve rate. The lenders all incur a nonnegative transaction cost, λ. Sources of this cost can be the uncertainty associated with the auction process, *i.e.*, their efforts required to judge a borrower's creditworthiness, whether the ongoing interest rate reflects that quality, the need to observe the behavior of other investors

(Zhang and Liu 2012), and the fact that the loan may not be fully funded at the end. This cost λ therefore increases the lenders' minimum acceptable interest rate to $W_n + \lambda$. In other words, lenders will require higher interest rates than their true values to compensate for the transaction costs associated with the auction mechanism. We normalize λ to zero under posted prices, reflecting the idea that lenders in auctions incur strictly higher transaction costs than in posted prices.

In the private value paradigm, auction theory (Krishna 2009) predicts that the weakly dominant strategy for a lender is to submit their true value $W_n + \lambda$. Compared to models in the auction literature, our context presents two complications. First, lenders' bids are bounded above by the borrower's reserve interest rate. Second, lenders will take into account the loan's potential likelihood of default, which is closely related to the contract interest rate. However, it is straightforward to show that these two factors do not affect lenders' equilibrium bidding strategy, and their weakly dominant strategy is still to bid their true valuation. Thus, the winners will be the Q lenders with the lowest true WTL, and each of them wins one unit of the loan. Knowing the lenders' bidding strategy, the borrower will choose a reserve interest rate, r^*, to maximize their expected payoff. Before the regime change, this reserve interest rate corresponds to the initial interest rate set at the very beginning of the auction process.[6]

To develop the borrower's payoff function, we notice that this is a personal loan market with borrowing and repayment obligations in a future date. Specifically, if the loan is funded, the borrower receives Q units from the lenders immediately, but is also committed to pay back the principal and interest within a certain time period. Without loss of generality, we assume that this is a one-period loan. The total repayment amount will be $Q \cdot (1 + p_A(r) + c)$, where $p_A(r)$ is the market clearing interest rate if the loan is funded. The subscript indicates that the listing is funded from an auction, and this interest rate is a function of the borrower's reserve interest rate. If the borrower is risk neutral, then their payoff in terms of present value will be $\pi_A = Q - Q \cdot (1 + p_A(r) + c)/(1 + \tau)$, or as a function of r:

$$\pi_A = \frac{Q \cdot (\tau - p_A(r) - c)}{1 + \tau}.$$

It is clear that the market clearing interest rate will vary across listings. Specifically, the market clearing rates will be equal to

$$\begin{cases} w^{N:Q+1} + \lambda, & \text{if } w^{N:Q+1} + \lambda \le r; \\ r, & \text{if } w^{N:Q} + \lambda \le r < w^{N:Q+1} + \lambda. \end{cases}$$

[6] Recall that we assume the borrower's discount rate to be τ. We can interpret it as the interest rate of the borrower's best outside option, *i.e.*, the lowest rate he or she is offered from other financial institutions. Based on this interpretation, the borrower's reserve interest rate must satisfy $r < \tau$. Our results later confirm this observation.

The first case corresponds to the scenario where the lowest losing interest rate is less than the borrower's reserve rate, thus setting the price of the loan. The second case is where the reserve rate sets the price since no losing lender is willing to bid less than that rate. Note that the probability of being funded is $\Pr(W^{N:Q+1}+\lambda \le r)$ and $\Pr(W^{N:Q}+\lambda \le r < W^{N:Q+1}+\lambda)$ respectively. Then the expected market clearing rate $p_A(r)$ conditional on the reserve interest rate r will be $E[W^{N:Q+1}+\lambda|W^{N:Q+1}+\lambda \le r]$ and r, respectively. Therefore, we can write the borrower's expected payoff as

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

The borrower maximizes expected payoff by choosing the initial reserve interest rate r. It is straightforward to show that the optimal reserve interest rate r^* is defined by the implicit function below. We can interpret the ratio as the normalized premium deducted to rule out the possibility that the lowest losing bid is less than the reserve interest rate.

$$r^* = \tau - c - \frac{F_W(r^*-\lambda)}{Q\cdot f_W(r^*-\lambda)}. \tag{1}$$

An important implication of this result is that the optimal reserve interest rate is strictly less than the borrower's underlying maximum acceptable rate, $\tau - c$. This allows the borrower to secure a positive expected profit. We also recall that $F_W(\cdot)$ and $f_W(\cdot)$ are the distribution functions of lenders' values. The result implies that the optimal reserve price is independent of the number of lenders. If W_n has a log-concave distribution, r^* is increasing with the quantity Q.

3.2. (Platform-Mandated) Posted Prices

We now model the dynamics among borrowers, lenders, and the platform under the posted-price mechanism. Importantly, since Prosper.com sets the initial interest rate (p^*) under this new mechanism, rather than borrowers, we specifically consider the platform's incentive in pricing borrower loans to maximize its own expected profit. The borrower either accepts or rejects the interest rate that Prosper.com sets for their loan. If they accept, the interest rate will be fixed at that level.

Before we model Prosper.com's decision process, we consider a hypothetical setting where the borrower is able to choose the interest rate under posted prices. If the borrower could have chosen the fixed interest rate level, their expected payoff can be written as

$$E\pi_B = \frac{Q\cdot(\tau-p-c)}{1+\tau}\cdot\Pr\left(W^{N:Q}\le p-\delta(p)(1+p)\right),$$

where $\delta(\cdot)$ is the default rate function.The B subscript indicates that it is (for now) the borrower's choice. To see the inequality in the equation, notice that a lender will find the loan profitable if and only if $1 + w_n \leq (1+p)(1-\delta(p))$, which can be simplified to $w_n \leq p - \delta(p)(1+p)$. Let $\gamma(p) = p - \delta(p)(1+p)$, which is the loan's expected rate of return.

The borrower would maximize their revenue by choosing p. The following equation characterizes this optimal price level implicitly,

$$p_B^* = \tau - c - \frac{G_Q(\gamma(p_B^*))}{g_Q(\gamma(p_B^*)) \cdot \gamma'(p_B^*)}. \tag{2}$$

It can be shown that the relationship between p_B^* and the reserve interest rate r^* in auctions depends on the return function, $\gamma(\cdot)$, as well as the distribution of lenders' valuations. Under mild conditions, p_B^* is strictly less than r^*. This is an extension to Einav et al. (2013). Under the usual commodity economy interpretation, therefore, the seller assigns higher "price"—analogous to lower interest rate in our context—in the posted-price setting, given the common value setup.

We now return to Prosper.com's decision. The platform presets the interest rate p for a particular loan. The borrower's strategy is to pick a threshold or cut-off rate $\tilde{p}$. If p is lower than this cut-off, the borrower will accept the offer. If it is higher, they will reject it and leave the market. In other words, the borrower accepts p if $p \leq \tilde{p}$, and rejects it otherwise. Note that again the probability of being fully funded is $\Pr(W^{N:Q} \leq \gamma(p))$. Similar to our analysis of the auctions, the borrower's expected payoff for accepting Prosper.com's pre-set interest rate can be shown to be $\frac{Q\cdot(\tau-p-c)}{1+\tau} \cdot \Pr(W^{N:Q} \leq \gamma(p))$, while rejecting the offer generates zero payoff. At the threshold, the borrower is indifferent between accepting and rejecting. That is, $\frac{Q\cdot(\tau-p-c)}{1+\tau} \cdot \Pr(W^{N:Q} \leq \gamma(p)) = 0$. Then it is easy to show that the cutoff price is $\tilde{p} = \tau - c$.

Suppose now that the platform knows the borrower's true cost c and discount rate τ, and thus $\tau - c$.[7] Prosper.com's profit comes from the fees that it charges on funded loans. We let α denote this closing fee. This fee is fixed, in the sense that Prosper.com does not change it in the short run (consistent with what we observe for our study period). Then we can write down Prosper.com's expected profit as

$$E\pi_P = \alpha \cdot Q \cdot \Pr\left(W^{N:Q} \leq \gamma(p)\right).$$

Prosper.com chooses an interest rate to maximize this profit given $p \leq \tau - c$ and $p \geq 0$. It can be shown that the following assumption is a sufficient condition under which Prosper.com assigns the highest possible interest rate, *i.e.*, $\tau - c$.

[7] To see why this is a reasonable assumption, notice that we interpret τ as the borrower's lowest interest rate from their outside options. As a professional financial organization, Prosper.com has the whole set of credit information necessary to derive the interest rate that the borrower is able to obtain from other channels.

ASSUMPTION 1. The hazard rate for the default rate function, $\delta^{'}(p)/(1-\delta(p))$, is bounded above by $1/(1+\tau-c)$, *i.e.*, for all $p\in[0,\tau-c]$,

$$\frac{\delta^{'}(p)}{1-\delta(p)}\leq\frac{1}{1+\tau-c}.$$

Assumption 1 adds some functional form restrictions but remains fairly reasonable and intuitive. Under this assumption, we can show that $\Pr(W^{N:Q}\leq\gamma(p))$ is a nondecreasing function of p.[8] This implies that Prosper.com will choose an interest rate as high as possible to maximize its expected profit. To summarize, in a posted-price setting Prosper.com presets an interest rate,

$$p^{*}=\tau-c. \tag{3}$$

3.3. Comparisons and Predictions

An immediate observation is that $p^{*}>r^{*}$. In other words, Prosper.com will preset an interest rate higher than what the borrower would have chosen in auctions. Also note that the probability of being funded in the auctions, $\Pr(W^{N:Q}+\lambda\leq r^{*})$, is strictly less than that under posted prices, $\Pr(W^{N:Q}\leq\gamma(p^{*}))$.[9] Conditional on the loan being funded, since the initial interest rate in the posted-price regime is higher than that in the auctions, and the contract rate is identical to the initial rate under posted prices, the contract rate is also strictly higher than the contract rate in auctions. In turn, the loan default rate, which the finance literature has shown to be increasing in contract interest rates, should also be higher in the posted-price regime. We therefore summarize the following hypotheses from the model:

HYPOTHESIS 1 **(H1)**. *All else equal, the initial interest rates assigned by Prosper.com under the posted-price mechanism are* higher *than the initial interest rates chosen by borrowers in auctions.*

HYPOTHESIS 2 **(H2)**. *Conditional on loans being funded, the contract interest rates under the posted-price mechanism are* higher *than those under the auction regime.*

HYPOTHESIS 3 **(H3)**. *The funding probability under the posted-price mechanism is* higher *than in auctions.*

HYPOTHESIS 4 **(H4)**. *For funded loans, the probability of default under the posted-price mechanism is* higher *than in auctions.*

[8] Note that Assumption 1 is a sufficient condition for the return function, $\gamma(\cdot)$, to be nondecreasing on $[0,\tau-c]$.

[9] A necessary condition is $\delta(\tau-c)\leq(\tau-c)/(1+\tau-c)$, which suggests that unless the default rate is too high, the funding probability under the posted-price regime is strictly higher.

In addition to these predictions, for the higher initial interest rate to induce higher funding probabilities, we should observe that lenders are more likely to bid under posted prices. Hence, an auxiliary hypothesis is that lenders should be likely to place bids earlier in auctions, and place larger bids, in the new regime. And because the price information (interest rate) from Prosper.com should carry more weight than the asking rate of borrowers, lenders should be able to rely less on the behaviors of others to judge borrower quality. Therefore, the herding behavior documented in Zhang and Liu (2012) should be reduced, if not eliminated, under posted prices. However, our focus remains the four hypotheses above.

3.4. Intuitions for the Stylized Model

Although we derived the hypotheses from a stylized model, the intuitions behind them are straightforward. Under both regimes, the borrower moves before the lenders, as the borrower needs to commit to an initial interest rate before lenders decide whether or not to invest. The website's profit comes from originated loans. In addition, there are two key features for the posted-price mechanism. First, the pricing power lies with Prosper.com. Second, by serving as the pricing agent, Prosper.com reduces the uncertainty associated with ongoing interest rates in auctions.

Under auctions, the borrower is faced with a tradeoff between the initial (asking) interest rate and probability of funding. The borrower will favor a lower starting interest rate because they cannot revise that rate once the auction starts, and if the rate is unnecessarily high, that rate will be effective for the life of the loan (*cf.* "winner's curse"). In fact, if the lower rate does not attract sufficient funding, it is virtually costless to post another request with a higher asking rate. Under posted prices, Prosper.com implicitly signals that the interest rate reflects borrower quality. In other words, at the same starting interest rate, lenders will be more likely to place bids under posted prices than auctions. Prosper.com is therefore able to extract surplus from the borrower because the borrower has to move first, and by setting the interest rate higher, Prosper.com will entice potential lenders to participate and fund loans—after which the website is able to charge fees. This is the intuition behind hypothesis 1, and the other hypotheses follow.

We now turn to transactions data from Prosper.com to empirically test these hypotheses.

4. Data

We obtained data from Prosper.com on January 14, 2013. The dataset contains all transactions since the website's inception in 2006, including both funded and failed listings. For each listing, we obtain an extensive set of variables including the requested amount, initial interest rate, loan term, starting and ending time, result, and repayment status as of our data collection date (if funded). The borrower's credit information includes their Prosper rating (a letter grade indicating the borrower's creditworthiness), debt to income ratio, as well as extended credit information such as the number of credit lines, delinquency history, and bank card utilization. We also obtain detailed information for each bid, including the identity of the lender, bid amount, bid time, and outcome (winning or losing). Finally, for successfully funded loans, we have the loan origination date, contract interest rate, repayment status each month, and so on.

Prosper.com eliminated auctions on December 20, 2010. We therefore construct our main sample to include all listings that are posted between August 20, 2010 and April 19, 2011, except those suspected of borrower identity theft and repurchased by Prosper.com.[10] During this period, the regime change under investigation was the only major policy change on the platform.[11]

Tables 2 and 3 summarize the main sample. There were $13,017$ listings posted during the period. $8,470$ of them began before December 20, 2010, and $4,547$ listings were initiated in the posted-price regime. Out of these listings, $4,446$ were funded and became loans. Among them, $1,925$ were funded using auctions, and $2,521$ were funded under posted prices. We also include summary statistics of some additional variables about macroeconomic conditions, which we will discuss in detail later. We further depict the daily average quantities of the four outcome variables in Figure 1. We observe that the daily ratio of funded and defaulted loans both increase after the regime change, and that the average asking interest rates and contract interest rates for funded loans both decline under posted prices without controlling for any covariates. We also find 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 regime; this is consistent with the website's claim for "quicker deployment of funds" as a rationale for the regime change. To more formally test the hypotheses derived in Section 3, we estimate how funding probabilities, interest rates and default rate change as a result of the regime change, holding listings characteristics constant.

5. Empirical Analyses and Results

We now empirically test the hypotheses discussed earlier. Since funding probability and contract interest rate of funded loans are immediate results of lenders' behaviors, our analyses will not be complete without a finer look into the lenders' behaviors, such as the amount and timing of bids, and if the regime change resulted in any changes in their herding behavior (Zhang and Liu 2012).

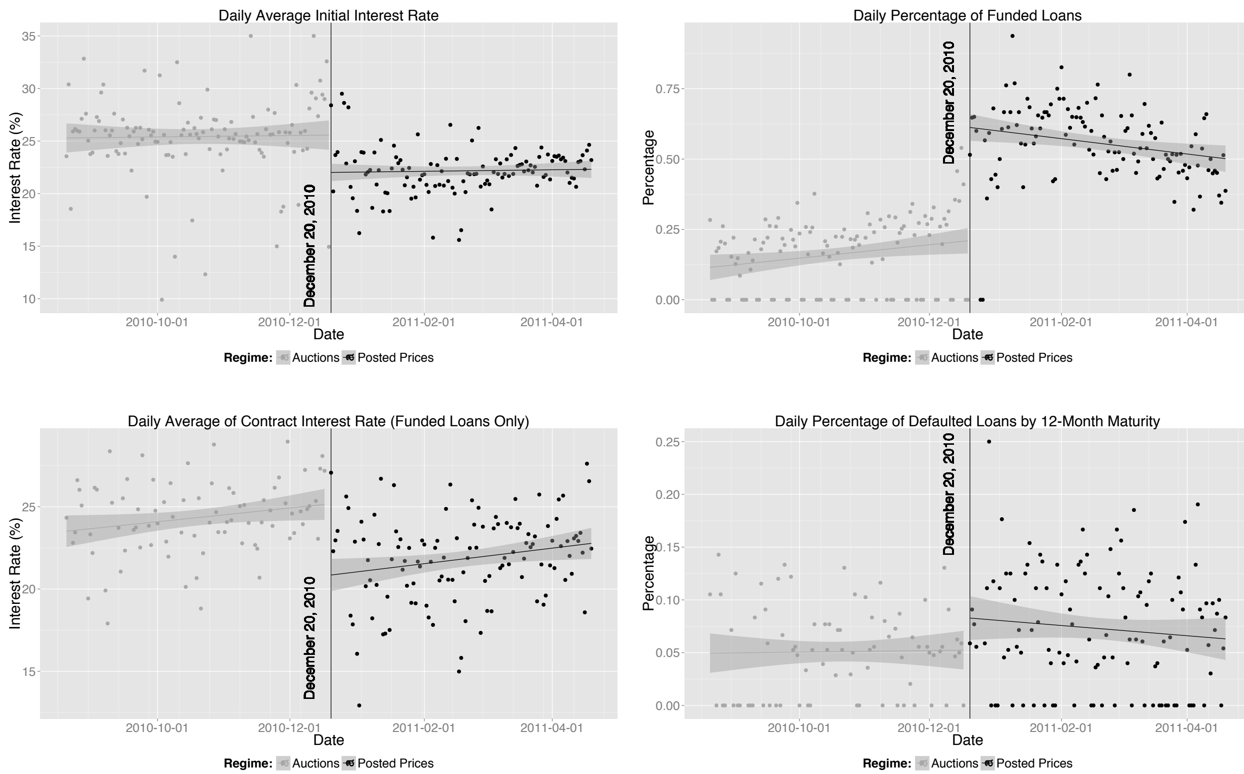
5.1. Empirical Strategy

Our model predicts that Prosper.com, in the posted-price regime, will assign higher interest rates compared to what the borrower would have chosen as the reserve interest rates in auctions, *ceteris*

[10] Prior to August 2010, Prosper.com allowed borrowers to use "automatic funding" for their auctions, where the borrower sets a reserve interest rate and the auction process would end as soon as 100% funding was reached. This funding option was discontinued by the website, and during the time that we study, no such auctions existed.

[11] Prosper.com also extended listing durations from 7 days to 14 days. As we will show later in Section 6.1.2, this is highly unlikely to be driving our findings.

Figure 1 Daily Transaction Outcomes before and after the Regime Change



paribus. Further, the *contract* interest rates (for funded loans), funding probability, and default rate should all be higher under posted prices. Before we empirically test these hypotheses, we notice that borrowers under posted prices have better credit (see Tables 2 and 3, as well as Figure 2): The fraction of borrowers with better credits is significantly higher than before. We further notice that the drop in the number of posted listings (as in Table 2) is mainly due to the decrease in the number of high risk borrowers. Our empirical strategy therefore has to account for such changes by controlling for borrowers' credit profile, loan and listing characteristics, and other covariates.

The key variables we control for in our estimations are summarized in Tables 2 and 3. In addition to these variables, we further control for the creditworthiness categories of borrowers as specified by Prosper.com. The categorical pricing system shown in Figure 3[12] illustrates how Prosper.com sets the interest rate for borrowers of different categories, and we control for borrower category in the same manner.

Our main empirical strategy is propensity score matching. Specifically, we consider the posted-price mechanism as the "treatment." Therefore, listings and loans under posted prices are in the *treatment* group, whereas those under auctions are in the *control* group. We estimate the

[12] This is a screenshot of Prosper's pricing table on September 26, 2011, taken from Archive.org. Prosper.com updates this table from time to time. More information can be found at `http://www.prosper.com/loans/rates-and-fees/`.

Table 2 Summary Statistics: All Listings

	All Listings[a]		Auctions		Posted Prices			
Variable	**Mean**	**sd**	**Mean**	**sd**	**Mean**	**sd**	t-stat	p-value
Listing Characteristics								
# of Bids	70.84	93.88	58.24	94.39	94.32	88.27	-21.70	< 0.01
1(Loan Funded)	0.34	0.47	0.23	0.42	0.55	0.50	-37.76	< 0.01
1(Electronic Transfer)	0.99	0.08	0.99	0.10	1	0	-8.99	< 0.01
1(With Description)	0.10	0.05	0.10	0.04	0.10	0.05	1.19	0.88
1(Group Member)	0.05	0.21	0.05	0.22	0.04	0.19	3.47	1
1(With Images)	0.16	0.37	0.24	0.43	0.002	0.05	51.07	1
Amount Requested	6,589.45	4,368.21	6,105.62	3,953.51	7,490.71	4,926.06	-16.34	< 0.01
Estimated Loss (%)	13.66	8.58	15.86	9.29	9.55	4.89	50.74	1
Initial Interest Rate (%)	24.32	9.27	25.58	9.35	21.98	8.64	22.04	1
Listing Effective Days	7.83	6.46	7.05	5.26	9.29	8.05	-16.93	< 0.01
Loan Term in Months	36.74	6.11	36.20	2.79	37.74	9.53	-10.62	< 0.01
1(With Friends Bidding)	0.02	0.13	0.02	0.14	0.01	0.12	2.27	0.99
Length of Description	130.89	80.78	144.91	87.63	104.78	57.71	31.34	1
Credit Profiles								
1(Verified Bank Account)	1	0	1	0	1	0	–	–
Debt/Income (DTIR) (%)	21.29	44.72	22.07	46.13	19.82	41.94	2.82	0.99
1(Top Coded DTIR)	0.001	0.04	0.001	0.04	0.001	0.04	–	–
1(Missing DTIR)	0.17	0.38	0.19	0.40	0.13	0.34	–	–
1(Homeowner)	0.49	0.50	0.50	0.50	0.47	0.50	2.78	1
Amount Delinquent	1,012.45	6,724.71	996.73	5,719.38	1,041.74	8,278.70	-0.33	0.37
Bankcard Utilization (%)	50.53	33.93	53.12	34.56	45.70	32.15	12.23	1
Current Credit Lines	9.06	5.29	9.08	5.31	9.04	5.26	0.36	0.64
Current Delinquencies	0.42	1.22	0.46	1.28	0.34	1.10	5.66	1
Delinquencies Last 7 Yrs	3.11	8.25	3.121	8.21	3.10	8.31	0.13	0.55
Inquiries Last 6 Months	1.35	1.92	1.54	2.12	0.99	1.40	17.80	1
Length Credit History	5,939.49	2,964.23	5,843.95	2,915.02	6,117.46	3,046.12	-4.96	< 0.01
Open CreditLines	8.00	4.77	8.00	4.78	8.00	4.75	-0.11	0.46
Pub Rec Last 12 Months	0.01	0.14	0.01	0.13	0.02	0.15	-1.70	0.05
Pub Rec Last 10 Years	0.24	0.67	0.24	0.67	0.25	0.66	-0.13	0.45
Revolving Credit Balance	17,200.92	37,234.34	17,794.58	38,372.88	16,095.08	34,992.20	2.55	0.99
Stated Monthly Income	5,010.90	13,875.29	4,571.00	12,482.46	5,830.32	16,122.23	-4.58	< 0.01
Total Credit Lines	24.95	13.99	25.07	14.19	24.74	13.59	1.33	0.91
Total Open Accounts	6.16	4.30	6.10	4.30	6.27	4.31	31.34	1
Macroeconomic Environment								
Unemployment Rate	9.44	1.89	9.62	1.88	9.11	1.86	14.96	1
1(Miss Unemployment)	0.01	0.08	0.01	0.07	0.01	0.09	-1.74	0.04
Zillow Home Value Index	187,424.10	82,477.59	189,662.10	83,724.63	183,255.20	79,945.08	4.29	1
1(Miss Zillow Index)	0.02	0.13	0.02	0.13	0.02	0.14	-1.21	0.11
Observations	13,017		8,470		4,547			

[a] This table presents the summary statistics of the corresponding variables from all listings. We conduct two-sided t-test for each variable. The alternative is that the mean of the corresponding variable in the auction regime is less than that in the posted-price regime. Zillow.com calculates and publishes the data on a monthly basis. The data are available at `http://www.zillow.com/research/data/`.

treatment effect associated with the market mechanism change using nearest-neighbor propensity score matching. First, we estimate the following probability of being in the posted-price regime

Table 3 Summary Statistics: Funded Loans

Variable	All Loans Mean	All Loans sd	Auctions Mean	Auctions sd	Posted Prices Mean	Posted Prices sd	t-stat	p-value
Listing Characteristics								
# of Bids	123.20	97.55	140.51	108.45	109.97	86.03	10.15	1
1(Electronic Transfer)	1.00	0.05	1.00	0.07	1.00	0.00	-3.01	< 0.01
1(With Description)	1.00	0.04	1.00	0.02	1.00	0.05	1.93	0.97
1(Group Member)	0.06	0.23	0.07	0.26	0.04	0.21	3.54	1
1(Images)	0.12	0.32	0.27	0.44	0.001	0.03	26.21	1
Amount Requested	6108.74	4321.44	5234.43	4057.03	6776.35	4398.17	-12.11	< 0.01
Contract Interest Rate (%)	22.79	9.08	24.25	9.32	21.68	8.73	9.36	1
Estimated Loss (%)	10.37	6.09	11.61	7.22	9.42	4.85	11.47	1
Initial Interest Rate (%)	23.30	9.24	25.44	9.46	21.68	8.73	13.58	1
Listing Effective Days	7.69	5.93	6.32	3.18	8.74	7.19	-15.07	< 0.01
Loan Term in Months	36.48	7.03	36.25	3.36	36.66	8.86	-2.12	0.02
1(With Friends Bidding)	0.03	0.17	0.04	0.20	0.02	0.14	4.23	1
Length of Description	127.82	76.75	150.56	90.71	110.46	58.41	16.90	1
Closing Fees	210.82	140.18	180.55	125.32	233.92	146.41	-13.07	< 0.01
1(Defaulted by 540 Days)	0.09	0.28	0.08	0.26	0.09	0.29	-2.12	0.02
Credit Profiles								
1(Verified Bank Account)	1.00	0.00	1.00	0.00	1.00	0.00	–	–
Debt/Income (DTIR) (%)	19.77	33.48	19.68	31.32	19.84	35.05	-0.16	0.44
1(Top Coded DTIR)	6.75e-04	0.03	5.20e-04	0.02	7.93e-04	0.03	–	–
1(Missing DTIR)	0.10	0.31	0.11	0.32	0.10	0.30	–	–
1(Homeowner)	0.51	0.50	0.52	0.50	0.50	0.50	1.49	0.93
Amount Delinquent	765.44	6035.19	661.71	4283.06	844.65	7087.08	-1.07	0.14
Bankcard Utilization (%)	50.73	32.59	52.88	33.07	49.09	32.13	3.83	1
Current Credit Lines	9.24	5.18	9.20	5.12	9.27	5.23	-0.45	0.33
Current Delinquencies	0.34	1.13	0.35	1.16	0.33	1.12	0.77	0.78
Delinquencies Last 7 Years	2.91	7.66	2.67	6.89	3.09	8.20	-1.89	0.03
Inquiries Last 6 Months	0.94	1.38	0.99	1.47	0.91	1.30	1.87	0.97
Length Credit History	5997.56	2821.95	5945.18	2843.14	6037.56	2805.56	-1.08	0.14
Open Credit Lines	8.15	4.67	8.10	4.64	8.19	4.70	-0.65	0.26
Pub Rec Last 12 Months	0.01	0.120	0.01	0.10	0.02	0.13	-1.38	0.08
Pub Rec Last 10 Years	0.26	0.65	0.26	0.64	0.27	0.67	-0.42	0.34
Revolving Credit Balance	16409.10	34784.77	16615.13	33808.10	16251.77	35518.38	0.35	0.64
Stated Monthly Income	5533.68	12454.72	5040.51	4108.85	5910.26	16136.82	-2.60	< 0.01
Total Credit Lines	25.43	13.56	25.21	13.61	25.60	13.53	-0.95	0.232
Total Open Accounts	6.26	4.19	6.21	4.13	6.30	4.23	-0.73	0.23
Macroeconomic Environment								
Unemployment Rate	9.32	1.87	9.59	1.85	9.11	1.86	8.54	1
1(Miss Unemployment)	0.01	0.08	0.01	0.08	0.01	0.09	-0.90	0.18
Zillow Home Value Index	185,355.00	80,456.74	187,407.40	82,348.41	183,787.80	78,962.31	1.48	0.93
1(Miss Zillow Index)	0.02	0.14	0.02	0.14	0.02	0.14	-0.08	0.47
Observations	4446		1925		2521			

(the treatment) given the set of covariates discussed above, using a logit regression,

$$\rho(\mathbf{x}_i) = \Pr\left(D_i = 1 | \mathbf{X} = \mathbf{x}_i\right), \tag{4}$$

where D_i is a dummy variable equal to 1 if the listing is posted after the regime change, and $\mathbf{X}$ includes all the covariates. Then we estimate the average treatment effects (ATE) with bias adjusted and robust standard errors. In other words, in matching we first find the nearest "neighbors"

Figure 2 **Distributions of Loans across Credit Grades Before and After Regime Change**

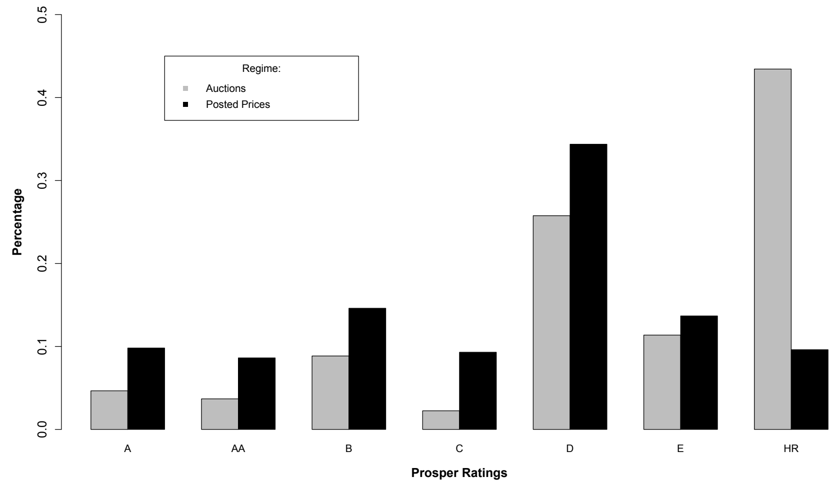


Figure 3 **A Sample of Prosper.com's Pricing Table after the Regime Change**

Prosper Rating	Term (yrs)	# Previous Prosper Loans	Borrower Rates	Borrower APR***
AA	1	1+	5.99%	6.93%
AA	3	1+	7.99%	8.33%
AA	5	1+	10.99%	11.21%
AA	1	0	5.65%	6.59%
AA	3	0	8.99%	9.33%
AA	5	0	11.99%	12.21%
A	1	1+	9.29%	15.08%
A	3	1+	11.29%	13.41%
A	1	0	10.70%	16.51%
A	3	0	13.90%	16.06%
B	1	0	14.99%	20.86%
B	3	0	17.99%	20.20%
C	1	1+	17.49%	26.44%
C	3	1+	18.99%	22.36%
D	1	1+	21.99%	31.04%
D	3	1+	23.99%	27.47%
D	1	0	24.99%	34.11%
D	3	0	26.99%	30.53%
E	1	1+	26.69%	35.84%
E	3	1+	30.99%	34.62%
E	1	0	26.69%	35.84%
E	3	0	31.99%	35.64%
HR	3	1+	31.25%	34.89%
HR	3	0	31.99%	35.64%

in the auction regime (untreated) for each listing under the posted-price mechanism (treated) in terms of propensity score, and vice versa. We then estimate the sample ATE with replacement. We follow Abadie and Imbens (2006) to calculate the standard errors of the matching estimates. All estimations are performed in R (Sekhon 2011).

5.2. Results and Discussions

5.2.1. Funding Probability and Interest Rates We report the results of our matching estimations in Table 4. Panel (1) of Table 4 reports the estimates for the comparison of *initial* interest rates. Estimates for the comparison of funding probability are reported in Panel (2). Panel (3) in Table 4 presents the results for the comparison of *contract* interest rates for the subsample of funded loans. In addition to the matching method, we also estimate simple linear regressions using ordinary least squares (OLS) for all outcomes (except contract interest rate where a Heckman model is required since only funded loans report contract interest rates), and Logit regressions for funding probability and default rate. Results (shown in Table 7) on the regime change effect are highly consistent with our matching estimates.

Our empirical results lend supports to our hypotheses about the comparisons of asking interest rates, funding probability, as well as the contract interest rates if funded. The matching estimate for the ATE of the regime change in Table 4 shows that in posted-price sales, the initial interest rate is around 1%, or 100 basis points, higher than what the borrower would have set in auctions. This is a nontrivial difference for interest rates (*cf.* Saunders, Jr (1993)). Notice that had we not controlled for the interest rate categories, the results would have been the opposite.

Table 4 Matching Estimates of the Regime Change Effects on Main Transaction Outcomes

	Matching estimates ($M = 4$)[a]							
Dep. var.:	*Initial* interest rate[b]		1(Loan funded)		*Contract* interest rate		1(Defaulted)[c]	
	(1)		(2)		(3)		(4)	
1(Posted Prices)	-1.036***	1.076***	0.325***	0.308***	0.078	0.726**	0.018*	0.025**
	(0.155)	(0.114)	(0.010)	(0.012)	(0.714)	(0.329)	(0.010)	(0.010)
Covariates:								
Personal loan characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Borrower's credit profile	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Macroeconomic environment	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Interest rate categories		Yes		Yes		Yes		Yes
Num. obs.	13,017	13,017	13,017	13,017	4,446	4,446	4,443[d]	4,443

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

[a] This table presents the nearest-neighbor propensity score matching estimates of the regime change effect on transaction outcomes. M is the number of matches to be searched. Typically the rule of thumb for M is 3 or 4. The standard errors are calculated by the method suggested in Abadie and Imbens (2006). All matching estimations are performed in R (Sekhon 2011).

[b] In auctions, borrowers set the initial interest rates. These are borrowers' *reservation* rates. In posted prices, Prosper.com presets the initial rate. It is fixed over the whole funding process.

[c] We examine the payment results by the 18th cycle (or month) since loan origination. Results are highly similar if we use 6th or 12th cycle maturity.

[d] Three observations are dropped because of incomplete records.

For the funding probability, Table 4 shows that compared to using auctions, the funding probability using the price posting strategy is on average more than 30% higher. The top right panel in

Figure 1 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.[13]

Estimates in Panel (3) of Table 4 imply that after the regime change, the *contract* interest rates for funded loans are around 0.7% higher than the loans funded in auctions. These results lend support to our theoretical prediction that the *contract* interest rates should be higher in the posted-price regime. They show that while the loans were more likely to be funded under posted prices, it came at a cost in the form of higher interest rates. All results above are robust to the choice of different matching estimators. Similar results hold when we estimate the average treatment effect on the treated (ATT) for all three outcome variables.

5.2.2. Loan Repayment 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 materialize. If lenders' choices turn out to be wrong, that could hurt their incentive to continuously participate in the market. Our Hypothesis 4 is that the default rate will be higher under posted prices, and we test it next.

Since some loans originated in this period have not yet matured as of the time of writing, we compare the repayment of loans in two ways. First, we record loan repayment status as of the 18th payment cycle (month) since their origination date. This ensures that we are comparing loans at a similar stage of "maturity." The base rate of default at the 18th cycle for the whole sample is 9.92%. We find that 8.62% of loans originated in auction stage default at the 18-month maturity, whereas this ratio is 10.91% for posted prices.

We then estimate whether the regime change is associated with a higher or lower default rate, and present the estimation results in Panel (4) in Table 4. Our results are robust to the choice of different repayment dates. Consistent with Hypothesis 4, we find that loans originated after the regime change have *higher* default rates: roughly 2.5% higher than in auctions. This is a subtle but important consequence of the regime change.[14] It suggests that even though lenders see a higher

[13] One may argue that the kink could be driven by seasonality effect since the regime change was made right before the Christmas holiday. We check that possibility by examining the daily ratio of funded loans one year prior to our study period (when there was no regime change), and do not find such an effect of seasonality.

[14] One may be concerned that after the regime change the lenders race to secure a fraction of the loan before full funding, and this competition effect may encourage risk taking behavior among lenders, which in turn causes the higher default rate. However, this is unlikely to be driving our results. First, we observe that the median credit grade of lenders' investment was actually *higher* after the regime change, meaning more funds were invested in less risky loans. Second, this scenario is akin to herding. Our results later in the paper actually shows that herding is in fact *lower* under posted prices. In particular, even if we look at listings at the lowest credit grade, herding is still lower than under auctions. Last but not least, we also conduct another analysis (regression and matching yield similar results) with the outcome being whether the loan defaults at the end, and the independent variable is how much time (in hours) it took the loan to reach full funding; we also control for all other variables as before. If the "frenzy" suggested by this scenario leads to irrational behavior, then loans that were funded faster (more eager investors) should be more likely to default. The result contradicts this: the time variable is not significant at any level. For brevity we do not report these results here.

interest rate at the time of loan origination, their overall return is not necessarily higher, due to the increase in *ex post* default probabilities.

The second method that we use to compare loan performance is a survival analysis of a loan's time-to-default (Lin et al. 2013). We study the effects up to various maturity dates as the previous method, and results are highly consistent. Results are shown in Table 5. Estimates in the table are the exponentiated estimates from a Cox proportional hazard regression. Results from the main specification (Spec 5 in the table) suggest that after the regime change, the hazard rate of default[15] increases by 50.4%. Taken together, our findings indicate that loans funded under posted prices are indeed more likely to default, consistent with our hypothesis.

Table 5 Cox Estimates of a Competing Risks Model for Loan Repayment

	Cox proportional hazard estimates[a]				
	Spec 1	Spec 2	Spec 3	Spec 4	Spec 5
exp (**Coef. of 1(Posted Prices)**)	1.250^{**}	1.371^{***}	1.396^{***}	1.417^{***}	1.504^{***}
	(0.102)	(0.108)	(0.110)	(0.110)	(0.111)
Covariates:					
Personal loan characteristics		Yes	Yes	Yes	Yes
Borrower's credit profile			Yes	Yes	Yes
Macroeconomic environment				Yes	Yes
Interest rate categories					Yes
Num. obs.	4,446	4,446	4,446	4,446	4,446

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

[a] This table presents Cox proportional hazard estimates of a competing risks model for the duration of the funded loans' repayment on Prosper.com. Specifically, we model the length of time until a loan being defaulted, and define a loan as defaulted if the status shows either over 4 months late, defaulted, or charge-off. We treat early payoff as a competing "risk" of terminating the loan repayment process. We compare loans' repayment up to 540 days since their origination dates, thus loans still in payoff progress are right-censored. Estimations are performed in R (Scrucca et al. 2007).

5.2.3. Lenders' Bidding Behaviors While the focus of our paper is the effect of regime change on loan outcomes, our understanding of the market mechanism's impact will not be complete without characterizing how investors respond to the regime change. The goal of this section is to investigate if the impact on investor behavior is consistent with—and therefore further lend support to—our findings on loan-level outcomes.

We study the change in lender's bidding behaviors from two aspects. The first one uses each bid as the unit of analysis to compare the *timing* of lenders' bids as well as the *amount* of their bids. The second one draws on published studies of *herding* in the context of Prosper.com (Zhang and Liu 2012), and tests whether the regime change affects lender's tendency to follow each other.

[15] In the main specification, we define a loan being defaulted if the status shows "4+ months late," "defaulted," or "charge-off." For robustness, we tried changing the definition of default to being late and beyond, 1 month late and beyond, 2 month late and beyond, or 3 month late and beyond. Cox estimates from all these extensions are qualitatively similar.

Figure 4 Distribution of Average Bid Amount across Listings Before and After Regime Change

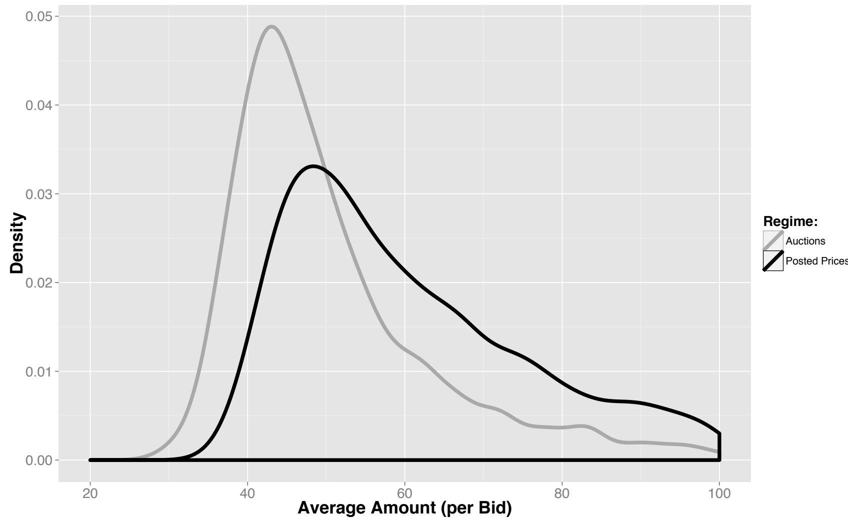


Figure 4 presents a comparison of the dollar amount in each bid. It shows that under posted prices, lenders tend to invest more in each bid than they do under auctions. As a result, the median number of days to reach full funding is 80 hours under posted prices, compared to more than 160 hours for auctions. Both results are consistent with our prior finding that loans are funded faster under posted prices.

Another important characterization of lender behavior is herding. Since lenders are more likely to trust the starting price assigned by the platform than by borrowers, lenders will have *lower* needs to wait and observe the behaviors of others. Therefore herding should be less likely to occur under posted prices. To test this, we draw on prior empirical work by Zhang and Liu (2012) who also used data from Prosper.com, and estimate their models using listings from both regimes. Estimation results (6) show an interesting *reversal* 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), confirming our expectation. This again is consistent with our earlier finding that loans are funded faster under posted prices: Lenders do not need to wait to observe peer actions, so they bid sooner, and bid more.

6. Robustness and Additional Tests

6.1. Robustness

We conduct a large number of tests to ensure that our main results are robust and not due to alternative explanations. We explore sensitivity of our matching estimator; linear regression estimator rather than matching; potential confounding effect of listing duration change; composition of lenders and their behaviors; as well as alternative samples. Our results remain highly consistent.

Table 6 Comparison of Herding Behavior

	Within Estimates[a]	
Dep. var.: Daily fund received	Auctions	Posted prices
Lag Cum Amount	0.027^{*}	-0.172^{***}
	(0.014)	(0.018)
Lag Percent Needed	-0.005^{***}	-0.003^{***}
	(0.000)	(0.001)
Lag Min Rate	-0.098^{***}	
	(0.022)	
Lag Bids	-0.001	0.015^{***}
	(0.001)	(0.001)
Lag Cum Amount * Lag Percent Needed	0.001^{***}	0.008^{***}
	(0.000)	(0.000)
Listing FE	Yes	Yes
Day of Listing FE	Yes	Yes
Weekday FE	Yes	Yes
Adj. R^2	0.090	0.252
Num. obs.	24,773	21,366

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

[a] This table presents the within estimates of a panel model that explores the correlation between the funds received in a day, and the total funds received by the end of previous day. Full descriptions and justifications can be found in Zhang and Liu (2012). Note that the listings sampled in this table include only those with at least one bid.

6.1.1. Empirical Model Robustness Propensity score matching sensitivity: The propensity score matching method that we use relies on the assumption of selection on observables, and a common concern for this method is that unobservables may be driving the difference between treatment and comparison groups. In order to investigate how sensitive our matching estimates are to the possible presence of an unobserved confounding variable, we conduct sensitivity analysis (Rosenbaum 2002). We find that in order for the regime change effect to disappear, the unobserved confounder has to change the odds of selection into the treatment by at least 30% for all outcomes. This is therefore unlikely a first order concern in our analysis.

Alternative specifications: As an alternative to matching methods, we re-estimate the regime change effects on interest rates, funding probability, and default rates using linear models. The specific equation we estimate is:

$$y_{ir} = \nu_r + \beta_1 1(\text{Posted Prices})_{ir} + \beta_2' \mathbf{X}_{ir} + \epsilon_{ir}, \tag{5}$$

where y_{ir} are the transaction outcomes of initial interest rates, indicator of full funding, contract interest rates if funded, or the indicator of default for funded loans; ν_r are the interest rate category fixed effects as discussed in Figure 3; $\mathbf{X}_{ir}$ are the control variables in Equation 4. The coefficient of interest is β_1 of which the estimates are the regime change effects.

We report estimation results using our main sample in columns 1, 2, 4, and 6 of Table 7. The estimates are qualitatively consistent with our findings in matching except for contract interest rates. However, the linear model for interest rate is biased due to a selection process, since only funded loans have data on interest rates. In auctions, given an interest rate category, loans with higher interest rates are more likely to be funded. In addition, the variation of interest rates within each category is larger under auctions. We therefore estimate a Heckman selection model using the two-step method(Lin et al. 2013). Results are reported in column 5 of Table 7. The estimate of the regime change effect, β_1, is again positive and consistent with the matching estimate. For comparisons of funding probability and default rate, we also estimate Logit models in view of the dichotomous dependent variables. Results are reported in columns 3 and 7 in Table 7. Estimates of the regime effects are in the same direction as our matching estimates.

Table 7 Comparisons of Transaction Outcomes using Linear Regressions

	Transaction Outcomes[a]						
Dep. var.:	*Initial* interest rate	1(Loan funded)		*Contract* interest rate		1(Defaulted)	
	OLS	OLS	Logit	OLS	Heckman[b]	OLS	logit
1(Posted Prices)	1.181^{*}	0.255^{***}	0.210^{***}	-0.414^{*}	0.701^{**}	0.032^{*}	0.029^{*}
	(0.592)	(0.014)	(0.015)	(0.237)	(0.341)	(0.018)	(0.017)
Covariates:							
Personal loan characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Borrower's credit profile	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Macroeconomic environment	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Interest rate categories	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.735	0.242	-	0.953	-	0.086	-
Pseudo R^2	-	-	0.211	-	-	-	0.144
Num. obs.	13,017	13,017	13,017	4,446	13,017	4,443	4,443

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

[a] This table displays estimation results of linear models for all transaction outcomes. For comparisons of funding probability and default rate at 18-cycle maturity, we also estimate Logit models. Similar results show up for probit models. Robust standard errors (in all models) are present in the table.

[b] For the comparison of contract rates, there is a selection issue that in auctions the loans with higher reserve rates are more likely to be funded, even if we control for all observed characteristics. Thus we also estimate a Heckman selection model using two-stage least squares.

6.1.2. Alternative Explanation: Funding Duration? Along with the regime change, Prosper.com also extended the funding duration for all listings after December 20, 2010 to 14 days (it used to be 7 days before that). It appears plausible that longer durations may explain some of our findings, especially the increased funding probability. To examine this possibility we take several different approaches: summary statistics; a survival analysis; and evidence from a previous exogenous event (unrelated to the market mechanism change) on duration that also occurred on Prosper.com.

We first examine whether the extended duration was indeed a *binding* constraint on the funding process, or the extent to which the longer duration actually helped more loans receive full funding. We find that after the regime change, about 70% of loans were still funded within 7 days. Further, as we show in Section 5.2.3, more than half of posted-price loans were funded within 80 hours, which is significantly less than 7 days.

Second, to better take into account that the funding duration *can* be different under the two regimes, we model the funding process using a survival analysis. Specifically, we estimate a Cox competing risks model where t_0 is the start of a listing, and the dependent variable is the length of time to full funding. The main censoring event of interest is full funding. Table 8 reports the exponentiated estimates from the Cox regressions. The main specification, Spec 5 in the table, suggests that after the regime change, the hazard rate of being funded increased by a factor of 2.422, or, by 142.2%. This significant change in funding rate is consistent with our main findings of higher funding probability, and further implies that the posted-price loans were indeed quicker to fund even if we account for the funding duration difference.

Table 8 Cox Estimates of a Competing Risks Model for the Duration of Prosper Loans' Funding Processes

	Cox proportional hazard estimates[a]				
	Spec 1	Spec 2	Spec 3	Spec 4	Spec 5
exp(**Coef. of 1(Posted Prices)**)	2.380^{***}	2.796^{***}	2.627^{***}	2.632^{***}	2.422^{***}
	(0.030)	(0.035)	(0.036)	(0.036)	(0.037)
Covariates:					
Personal loan characteristics		Yes	Yes	Yes	Yes
Borrower's credit profile			Yes	Yes	Yes
Macroeconomic environment				Yes	Yes
Interest rate categories					Yes
Num. obs.	13,017	13,017	13,017	13,017	13,017

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

[a] This table presents Cox proportional hazard estimates of a competing risks model for the duration of funding process. Specifically, we model the length of time until a loan is fully funded, and we treat listing expiration or withdrawn by the borrowers as competing risks.

Third, to more directly investigate how duration changes could affect our outcome variables, we exploit an exogenous event related to funding duration (but unrelated to regime change that we focus on) to better tease out the causal impact of duration, if any. Prosper.com implemented another policy change on listing durations on April 15, 2008; before that date, borrowers can choose 3, 5, 7, or 10 days as the funding duration. Starting on April 15, 2008, the platform standardized durations for all listings to 7 days. This provides an ideal opportunity to evaluate the effects of funding durations. In particular since the confounding factor to our main analysis is an *increase* in funding duration, we focus on listings with 3- or 5-day durations prior to April 15, 2008, which were increased to 7 days due to the policy change. Our results[16] show that the variable on duration change is not statistically significant for any of the outcome variables. Therefore, the increase in duration is unlikely to be driving our main findings during the regime change. In fact, when we examine listings with 10-day duration (which would represent a *decrease* in funding duration), the result is also insignificant.

6.1.3. Alternative Explanation: Changes in Lender Compositions? Another concern is that our results may be driven by changes in the composition of lenders. We address this both conceptually (the first two points below) and empirically (the other three points). First, this would have been a plausible explanation if our data came from temporally or spatially disjoint samples, but we focus on data immediately around the regime change. Second, since we study the effect of market mechanisms, lender composition is more appropriately an outcome than an independent variable: Lenders arrive at listings *after* the market mechanism is public knowledge, and *after* the borrower's listing (including borrower information and loan characteristics) is revealed to all potential investors. To include lender composition into the right-hand-side of our models will introduce endogeneity and bias our results.

Third, despite the previous point, we nonetheless investigate whether considering the lender composition alters our findings. Specifically, we consider the composition using the proportion of participating lenders who had invested in at least 1 listing before the regime change. We repeat our matching estimations by including loan requests with at least 90% these "old" lenders. Results are presented in Table 9, and are highly consistent with our main findings.

Table 9 Matching Estimates of Regime Change Effect Considering Lender Compositions

	Matching estimates $(M=4)^a$			
Dep. var.:	*Initial* Interest Rates	1(Loan funded)	*Contract* Interest Rates	1(Defaulted)
1(Posted Prices)	1.011^{***}	0.319^{***}	0.468^{*}	0.018^{*}
	(0.119)	(0.013)	(0.265)	(0.011)
Covariates:				
Personal loan characteristics	Yes	Yes	Yes	Yes
Borrower's credit profile	Yes	Yes	Yes	Yes
Macroeconomic environment	Yes	Yes	Yes	Yes
Interest rate categories	Yes	Yes	Yes	Yes
Num. obs.	12,047	12,047	3,943	3,940

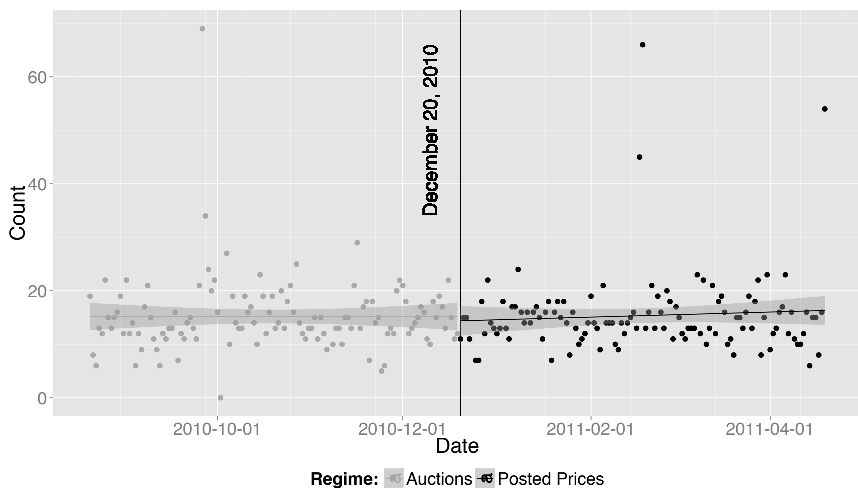
$^{***}p<0.01$, $^{**}p<0.05$, $^{*}p<0.1$

[a] Only loan requests with at least 90% lenders that participated before the regime change are included. Similar results appear for other thresholds such as 70% and 80%.

[16] Due to space constraints we do not report the results here, but they are available from the authors.

Fourth, there is no evidence that there is an influx of new (and potentially different) lenders after the regime change. The time series of the daily number of newly registered lenders shows no structural change before and after. Alternatively, when we compare the daily number of newly registered lenders before and after, a two-sample T-test rejects the null that the means of these two groups are different at any common significance levels. Figure 5 shows that the platform had a steady but relatively low level of growth on the supply side (of funds), with on average 18 new lenders joining per day.

Figure 5 Daily Number of Newly Registered Lenders Before and After the Regime Change



Last but not least, and also consistent with the previous point, the "old" lenders are still dominant in funding loans during our study period. In more than 90% of posted-price listings (with at least one investment), at least 80% of lenders were actually registered *before* the regime change. In other words, the proportion of funds from lenders that register after the regime change was largely ignorable. This ratio is even higher for funded loans, with almost all funded posted-price loans (98.69%) having at least 80% "old" lenders.

All the above evidence suggests that change in lender compositions is unlikely to be a plausible alternative explanation to our findings.

6.1.4. Alternative Samples Extended sample: Another potential concern is the sample used in our estimations. Our main sample contains all listings posted 4 months immediately before and after the regime change. As an alternative, we compare loans that were generated 4 months before the regime change, and those posted between April 20, 2011 and August 19, 2011—a larger window than our main sample. Matching estimates are reported in Table 10, and are highly similar to our main results.

Table 10 Matching Estimates of the Regime Change Effects using an Extended Sample

	Matching estimates $(M = 4)^a$			
Dep. var.:	*Initial* Interest Rates	1(Loan funded)	*Contract* Interest Rates	1(Defaulted)
1(Posted Prices)	3.007***	0.207***	2.511***	0.042***
	(0.270)	(0.045)	(0.612)	(0.007)
Covariates:				
Personal loan characteristics	Yes	Yes	Yes	Yes
Borrower's credit profile	Yes	Yes	Yes	Yes
Macroeconomic environment	Yes	Yes	Yes	Yes
Interest rate categories	Yes	Yes	Yes	Yes
Num. obs.	16,459	16,459	5,438	5,438

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

[a] Here we compare loans that were generated 4 months before the regime change, and those posted between April 20, 2011 and August 19, 2011.

"Interim" loans: The regime change we study is an overnight change, where all new listings that appear after midnight on December 20, 2010 use posted prices. Listings that were created prior to the change and were still open were included in our main analysis. However, our main results are virtually identical when we exclude them. There were only 144 such listings, and 40 of them were successfully funded. The interest rates of these loans were frozen at the time of the change, and the funding processes continued under the prevailing rates using the posted-price mechanism; they would be originated immediately when they receive 100% funding. In all previous empirical investigations, we include these loans as if they were under the auction regime (since their initial interest rates were not set by Prosper.com). To test whether our results are driven by these loans, we conduct a robustness check by *excluding* them. As Table 11 shows, results are highly consistent.

Table 11 Matching Estimates of Regime Change Effect Excluding "Interim" Loans

	Matching estimates $(M = 4)^a$			
Dep. var.:	*Initial* Interest Rates	1(Loan funded)	*Contract* Interest Rates	1(Defaulted)
1(Posted Prices)	1.107***	0.308***	0.888***	0.026***
	(0.115)	(0.011)	(0.304)	(0.010)
Covariates:				
Personal loan characteristics	Yes	Yes	Yes	Yes
Borrower's credit profile	Yes	Yes	Yes	Yes
Macroeconomic environment	Yes	Yes	Yes	Yes
Interest rate categories	Yes	Yes	Yes	Yes
Num. obs.	12,873	12,873	4,406	4,403

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

[a] We exclude "interim" loans that were still being funded at the time of the regime change.

6.2. Welfare Implications

Our results so far show that funding probability, interest rates, and default probability are all higher under posted prices. A natural and important follow-up question is whether the regime change is "better" for various stakeholders in this market. This question has important policy implications because it concerns social welfare, and we investigate it next. Our goal is to answer whether the overall social welfare is higher or lower under the new regime.

Although the posted-price mechanism brings higher funding probability, the higher contract interest rates will increase *ex post* default rates(Stiglitz and Weiss 1981). The total social surplus depends not only on how often the loans are being funded, but also on how often the funded loans are repaid. A welfare comparison should take both into account. We present a formal treatment of this analysis in Appendix A. Since the platform captures all borrowers surplus, borrowers' surplus should be decreasing, and the platform's surplus should be increasing.[17] In addition, the increase in platform surplus is no greater than the decrease in borrower surplus, otherwise the borrower would not find it profitable to borrow from the platform. However, the lender's surplus change is ambiguous because there is ultimately the tradeoff between higher nominal contract interest rates, and higher default likelihood. Our analysis in the appendix illustrates conditions under which auctions can generate *higher* social welfare than posted prices.

To further determine the net total surplus change, we need to empirically ascertain whether lenders' surplus is higher or lower under posted prices. We conduct two different analyses. First, we calculate the lenders' *return on investment* (ROI) using the loan performance data, thereby taking into account the influence of both the higher contract interest rate and higher likelihood of default. Lenders' ROI on a loan is calculated as *(Cumulative payment − Loan amount requested) / Loan amount requested*, which factors in the loan's repayment status. We can hence calculate each loan's ROI up to a certain billing cycle. We repeat our matching estimations and report the results in Panel (1) of Table 12. We find that after the regime change, the lenders' returns are significantly *lower* by about 3% by the 18-th cycle. Therefore, the higher probability of default dominates the positive effects of higher contract interest rates. This finding indicates that all else equal, lender surplus decreased after the switch to posted prices.

Second, we use a numerical approach to more directly and structurally calculate the change of lender surplus. To this end, the first step is to recover a representative lender's supply function. Such a function specifies a relationship between the lender's valuation of a loan (measured by the lender's lowest acceptable interest rate) and loan amount. We use $S(\cdot)$ to denote the supply function with $W = S(Q)$. We assume a simple functional form[18] of the supply function as $W = \alpha \cdot Q^{\gamma}$. We

[17] We calculated and compared the platform's revenue under auctions and posted prices, and found that platform surplus is indeed higher after the regime change. Detailed results are available from the authors.

[18] In our robustness checks, we allow for flexible functional forms including linear and higher-order terms. Results are highly similar.

Table 12 Matching Estimates for the Comparison of Lender Returns and Surplus

Dep. var.:	**Matching estimates** ($M = 4$)[a]			
	ROI (%)[b]		Lender surplus	
	(1)		(2)	
1(Posted Prices)	-0.031***	-0.029***	-46.637***	-43.676***
	(0.010)	(0.010)	(5.721)	(5.193)
Covariates:				
Personal loan characteristics	Yes	Yes	Yes	Yes
Borrower's credit profile	Yes	Yes	Yes	Yes
Macroeconomic environment	Yes	Yes	Yes	Yes
Interest rate categories		Yes		Yes
Num. obs.	4,443	4,443	4,446	4,446

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

[a] This table presents the nearest-neighbor propensity score matching estimates of the regime change effects on Lender ROI and surplus.

[b] We examine the ROI by the 18th billing cycle (or month) since origination. Similar results hold for 6th or 12th billing cycle.

take a log-transformation to obtain:

$$\log W = \log \alpha + \gamma \cdot \log Q. \tag{6}$$

With the supply function, the lender's surplus will be simply the area above this supply function but below the market transaction interest rate, factoring in the probability of default. We next empirically estimate the parameters of the supply function.

We use bids submitted to listings that are posted one year before our main sample (Section 4), between August 20, 2009 and August 19, 2010, to calibrate the supply function. We focus on open requests where the funding process continues after full funding. In open auctions, if and only if a bid is outbid will we observe its actual bid interest rate. We use these failed bids to uncover our parameters for the supply function. The identification of the supply function assumes that lenders are truthfully bidding by submitting their lowest acceptable interest rates. Since the auction on Prosper.com is essentially a second-price proxy auction, this assumption is reasonable. We further allow the representative lender to have different supply functions for loans in different credit grades. Therefore, we estimate one supply function for loans in each credit grade, ranging from AA (the best) to HR (the most risky). To estimate the expected probability of default, we run Logit regressions with the dependent variable being the dummy for loan default. We then use the predicted value from the Logit regressions as the proxy for the default rate. It is straightforward to calculate the lender surplus for each funded loan after estimating the supply functions. We find that the average lender surplus for loans under auctions is $35.95, while the average surplus for posted-price loans is -$29.49. We repeat matching estimations with the dependent variable the calculated lender surplus for a loan. Results are reported in Panel (2) in Table 12. Not surprisingly and consistent with our findings based on ROI, we find that the regime change *lowers* lender surplus. Therefore, as a result of the regime change from auctions to posted prices, borrower surplus is lower, platform surplus is higher (but not greater than the decrease in borrower surplus), and lender surplus is lower. The overall social welfare is therefore *lower* under posted prices.

6.3. "Soft" Information and Mechanism Change

Our focus in this paper is the effect of market mechanisms on typical transactional outcomes such as funding opportunities. But it is also plausible that market mechanisms may also affect the effectiveness of borrower's quality signals. One such signal that is unique to the crowdfunding context is "soft" information, *i.e.*, information about borrowers that are not captured in their formal credit reports but can be useful in these online markets to overcome information symmetry. For brevity, we focus on friendship network ties(Lin et al. 2013) as an example, and investigate whether and how their effectiveness changes after the change in market mechanism.

Consider the initial interest rate and the borrower's friendship network, both of which carry some information about the borrower's creditworthiness. However, the initial interest rate under posted prices is set by the platform rather than the borrowers themselves. It therefore implicitly serves as an "assurance" that this borrower's loan request *can* be priced and sold at this interest rate. By contrast, the initial interest rate in auctions does not have as much informational value. Therefore all else equal, the effect of having friends on funding success should be even *higher* under posted prices than in auctions, because the pricing information is independent of friendship ties (as discussed earlier, the interest rate in posted prices are set according to borrower's credit profile).

We test this conjecture by conducting subsample analyses. Specifically, we examine the effect of having Prosper.com friends for loans under auctions and posted-price loans separately and compare their marginal effects. Results are reported in Table 13. Consistent with our reasoning, we find that the effect size under posted prices are indeed *larger* than that in the auctions regime. Specifically, having friends on Prosper.com raises the funding probability by 12% under posted prices, but less than 7% under auctions.

7. Conclusions

The choice of market mechanisms is one of the most fundamental questions in any marketplace. For a nascent industry such as online peer-to-peer lending, or more broadly online crowdfunding, this choice is especially critical but not well understood. For crowdfunding market designers, platform owners and policymakers, there are delicate short-term and long-term consequences that should be carefully weighed. Although currently the two major peer-to-peer lending platforms in the US both use posted prices, many peer-to-peer lending platforms in other countries, as well as other types

Table 13 Matching Estimates: Effects of "Having Friends" on Funding Probabilities

	Before Dec. 20, 2010[a]			After Dec. 20, 2010		
Dep. var.: 1(Loan funded)	$M=1$	$M=4$	$M=8$	$M=1$	$M=4$	$M=8$
1(Having Friends)	0.078***	0.069***	0.065***	0.139***	0.122***	0.128***
	(0.025)	(0.020)	(0.020)	(0.038)	(0.035)	(0.034)
Covariates:						
Personal loan characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Borrower's credit profile	Yes	Yes	Yes	Yes	Yes	Yes
Macroeconomic environment	Yes	Yes	Yes	Yes	Yes	Yes
Interest rate categories	Yes	Yes	Yes	Yes	Yes	Yes
Num. obs.	8,470	8,470	8,470	4,547	4,547	4,547

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

[a] This table presents the matching estimates of the effect of "having friends" (on Prosper.com) on funding probability.

of crowdfunding platforms, still use auctions instead. More important, there is little systematic empirical evidence in favor of a particular mechanism, and the popularity of the posted-price mechanisms *per se* does not guarantee its efficiency or superiority. Our goal is to take a first step in fulfilling this gap in the crowdfunding literature.

To address this question, we first develop a stylized game theoretic model to compare uniform price auctions against posted-price sales, taking into account the incentive of the platform to maximize its own expected payoff. Then we test the model's predictions using detailed transactions data from Prosper.com, around the time of a unique regime change from auctions to posted prices. Our empirical results lend support to our hypotheses. Specifically, we find evidence of short-term improvements for both borrowers and lenders. Lenders benefit from a quicker "deployment" of funds because loans are more likely to be funded, and are funded faster under posted prices. Borrowers also *seem* to benefit from the new regime, since their requests are funded sooner. Both of these short-term benefits were noted by Prosper.com when they announced the regime change, and rightly so. The quicker deployment of funds into loans further translates into higher revenue for Prosper.com, and the platform's short-term surplus is unequivocally higher as a result.

On the other hand, however, as our theoretical model predicts and our empirical analysis shows, Prosper.com assigns higher initial interest rates under posted prices than borrowers would have in auctions. Hence, while lenders enjoy a higher *nominal* return on loans, it comes at a cost to borrowers. More important, this change has long-term implications for the repayment of loans. As the finance literature has long documented (Stiglitz and Weiss 1981), the interest rate is one of the most critical factors in determining *ex post* loan default. Our analysis of loans originated around the time of the regime change is consistent with this prediction, as we find that loans are indeed more likely to default under posted prices. Furthermore, welfare reduction due to increases in default actually *dominates* welfare increase from higher nominal interest rates, since lenders' overall return-on-investment (ROI) and surplus are *lower* under posted prices than auctions in our data. These findings, along with our analysis in Appendix A, suggest that overall social welfare is not necessarily higher with posted prices. Under some conditions in fact, the "slower" auctions may be better from a social planner's point of view.

Our paper is one of the first to systematically document some intended and unintended (and previously unknown) consequences of the regime change in online debt-based crowdfunding. While the traditional "crowd"-based auctions may be slower to fund loans, its long-term welfare is not necessarily worse than posted prices set by experts. Since peer-to-peer lending platforms deduct service fees at the time of the loan origination rather than repayment, it *is* in their best interest to ensure a higher funding probability in the short-term. However, borrowers, lenders, platforms and regulators will all be well advised to take into account the impact on long-term repayment, which may not receive as much attention as short-term benefits such as funding speed.

Our discussions here can be further extended to other types of crowdfunding. Even though the concept of initial interest rates may manifest itself in other variables for other crowdfunding formats, as long as the payoff function of platforms is short-term driven—*i.e.*, deduction of transaction fees at time of funding, be it debt-, equity- or reward-based crowdfunding—platforms will (not surprisingly) promote short-term success over long-term prospects. For a nascent industry, this is perhaps a "necessary evil" because platforms have to demonstrate their profitability to potential investors; the promise of crowdfunding to transform traditional finance and broaden access to capital will not materialize if platforms cannot even sustain themselves. But as the market matures and leading platforms become public companies, a longer-term orientation will serve the best interest of the platforms themselves as well as its stakeholders. One may argue that in the long run, investors will learn, and platforms ultimately will pay for the long-term lower performance. That however will crucially depend on a sufficient level of competition within the industry, which will be challenging due to the fact that these platforms are two-sided markets with significant positive network effects. While the choice of market mechanism will most likely always lie with the platforms, industry self-regulations or government oversight may be necessary in terms of either a more transparent pricing process (*i.e.*, the initial interest rate in our context), a revenue model that takes into account long-term performance (*e.g.*, linking platform revenue at least partially to debt repayment), or further innovations (*e.g.*, other market mechanisms).

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Appendix A: Welfare Comparison

In this appendix, we formally develop our discussion on the comparison of total welfare under the two market mechanisms. Mathematically, we decompose the total surplus of a particular loan into borrower surplus and lenders surplus, and compare them.

In the model described in Section 3, we assume that lenders in an auction incur positive transaction cost (λ), relative to the posted-price regime. An immediate observation is that this cost may induce efficiency loss, as the cost raises the lenders' minimum acceptable interest rates, which in turn lowers the funding probability. In other words, holding everything else equal (such as the borrower profile and lender population), the transaction cost associated with the auction mechanism reduces the total social surplus, as it raises the lenders' willingness to lend (supply function). Another key note is that in the posted-price environment, the borrower surplus is squeezed to zero: our model shows that under posted prices, Prosper.com assigns $p^* = \tilde{p}$, the maximum interest rate at which a borrower is willing to post the listing. Consequently, the lenders surplus is maximized under posted prices.

Let us first look at the total surplus for a listing under the auction mechanism. We consider a successfully funded loan with a default rate, δ. Let p denote the contract interest rate again, and then the default rate $\delta = \delta(p)$. We know that the borrower's highest acceptable interest rate is $\tilde{p} = \tau - c$ from our earlier results. We also know that with probability $\Pr\left(W^{N:Q+1} + \lambda \leq r^*\right)$ the contract interest rate is $p = W^{N:Q+1} + \lambda$ (where the lowest losing bid sets the contract rate), and with probability $\Pr\left(W^{N:Q} + \lambda \leq r^* < W^{N:Q+1} + \lambda\right)$, $p = r^*$.

We calculate the lenders surplus first. For a winner, since his minimum acceptable interest rate is generally lower than the contract rate, the individual surplus will be $(1 + w^{N:Q+1} + \lambda)\,(1 - \delta(p)) - (1 + w^{N:k} + \lambda)$ that is $w^{N:Q+1} + \lambda - \delta(p)(1 + w^{N:Q+1} + \lambda) - \lambda - w^{N:k}$, for k among the Q winners (lowest lenders) if the lowest losing bid sets the contract rate (Scenario I); $(1 + r^*)\,(1 - \delta(p)) - (1 + w^{N:k} + \lambda)$ that is $r^* - \delta(p)(1 + r^*) - \lambda - w^{N:k}$ for all k if the borrower's reserve interest rate sets the contract rate (Scenario II). All the other lenders fail to fund the loan, and thus have zero surplus. Then the total lenders surplus will be the sum over of all winners' surplus. The *ex ante* total lenders surplus (LS_A) can be shown to be equal to,

$$\begin{aligned}\mathrm{LS}_A = {} & E\left[\sum_{k=1}^{Q}\left[\gamma(W^{N:Q+1} + \lambda) - \lambda - W^{N:k}\right] | W^{N:Q+1} \leq r^* - \lambda\right] \times \Pr\left(W^{N:Q+1} \leq r^* - \lambda\right) \\ & + E\left[\sum_{k=1}^{Q}\left[\gamma(r^*) - \lambda - W^{N:k}\right] | W^{N:Q} \leq r^* - \lambda < W^{N:Q+1}\right] \times \Pr\left(W^{N:Q} \leq r^* - \lambda < W^{N:Q+1}\right).\end{aligned}$$

We then turn to borrower side. The borrower surplus, if the loan is successfully funded, will be $Q \times [(1 + \tilde{p}) - (1 + w^{N:Q+1} + \lambda)]$ that is $Q \times (\tilde{p} - w^{N:Q+1} - \lambda)$ in scenario I; and $Q \times [(1 + \tilde{p}) - (1 + r^*)]$ that is $Q \times (\tilde{p} - r^*)$ in scenario II. Then the borrower's *ex ante* surplus (BS_A) will be

$$\begin{aligned}\mathrm{BS}_A = {} & Q \times E\left[\tilde{p} - W^{N:Q+1} - \lambda | W^{N:Q+1} \leq r^* - \lambda\right] \times \Pr\left(W^{N:Q+1} \leq r^* - \lambda\right) \\ & + Q \times E\left[\tilde{p} - r^* | W^{N:Q} \leq r^* - \lambda < W^{N:Q+1}\right] \times \Pr\left(W^{N:Q} \leq r^* - \lambda < W^{N:Q+1}\right).\end{aligned}$$

The *ex ante* social surplus (TS_A) will be the sum of the total lenders surplus (LS_A) and the total borrower surplus (BS_A). It can be shown that the social surplus is equal to

$$\begin{aligned}\mathrm{TS}_A = & E\left[\sum_{k=1}^{Q}\left[\tilde{p}-\delta(W^{N:Q+1}+\lambda)(1+W^{N:Q+1}+\lambda)-\lambda-W^{N:k}\right]\Big|W^{N:Q+1}\le r^*-\lambda\right]\\ & \times \Pr\left(W^{N:Q+1}\le r^*-\lambda\right)+E\left[\sum_{k=1}^{Q}\left[\tilde{p}-\delta(r^*)(1+r^*)-\lambda-W^{N:k}\right]\Big|W^{N:Q}\le r^*-\lambda<W^{N:Q+1}\right]\\ & \times \Pr\left(W^{N:Q}\le r^*-\lambda<W^{N:Q+1}\right)\end{aligned} \tag{7}$$

Let us now conduct similar analysis for the posted-price mechanism. Previous result tells us that Prosper.com presets the interest rate that is equal to the borrower's highest acceptable rate, which is $p^*=\tilde{p}=\tau-c$. In this case the personal loan is funded if and only if $w^{N:Q}\le\gamma(p^*)=\gamma(\tau-c)$, or the Q-th lowest lender is willing to fund the loan. So a winning lender's surplus will be equal to $(1+p^*)(1-\delta(p))-(1+w^{N:k})=\gamma(p^*)-w^{N:k}$, for all $k=1,2,...,Q$ among the lowest lenders. Then the total lenders surplus is the sum of all lenders' surplus, which is $\sum_{k=1}^{Q}[\gamma(p)-w^{N:k}]$. The *ex ante* total lenders surplus (LS_P) is thus

$$\mathrm{LS}_P = E\left[\sum_{k=1}^{Q}\left[\gamma(\tau-c)-W^{N:k}\right]|W^{N:Q}\le\gamma(\tau-c)\right]\times\Pr\left(W^{N:Q}\le\gamma(\tau-c)\right),$$

where we define $\gamma(p)=p-\delta(p)(1+p)$ in Section 3.

As mentioned earlier, the borrower surplus in the posted-price mechanism is zero since Prosper.com presets the interest rate equal to his maximum willingness to borrow. Thus in this case the social surplus (TS_P) will be equal to the total lenders surplus, which we can show is equal to

$$\mathrm{TS}_P = E\left[\sum_{k=1}^{Q}\left[\gamma(\tau-c)-W^{N:k}\right]|W^{N:Q}\le\gamma(\tau-c)\right]\times\Pr\left(W^{N:Q}\le\gamma(\tau-c)\right). \tag{8}$$

First of all, given assumption 1, it can be shown that $\mathrm{LS}_p\ge\mathrm{LS}_A$. That is, the lenders surplus under the posted-price mechanism is at least as great as that in the auctions. In other words, the lenders are better off after the regime change.

More importantly, however, the regime change does not necessarily lead to higher total social welfare. It can be shown that under the following assumption, the total surplus in the posted-price selling (TS_P) is smaller than that in the auctions (TS_A).

Assumption 2. Let $p_A=\min\{r^*,w^{N:Q+1}+\lambda\}$, $\delta(\tilde{p})(1+\tilde{p})-\delta(p_A)(1+p_A)\ge\lambda$.

Note that $\delta(p)(1+p)$ measures a lender's expected loss , due to loan defaulting, at contract interest rate p. Thus, the left-hand-side of the inequality measures the difference in the expected loss under the two regimes. While the right-hand-side is the transaction cost that induces efficiency loss in the auctions. This assumption suggests that if the expected loss is reasonably high in the posted-price regime, the total social surplus will be less than that in the auctions. In this situation, the posted-price mechanism is dominated by the auctions.