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Market Mechanisms in Online Peer-to-Peer Lending

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Online peer-to-peer lending (P2P lending) 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 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 P2P lending platforms typically use one or the other, there is little systematic research on the implications of such choices for market participants, transaction outcomes, and social welfare. We address this question both theoretically and empirically. We first develop a game-theoretic model that yields empirically testable hypotheses, taking into account the incentive of the platform. We then test these hypotheses by exploiting a regime change from auctions to posted prices on one of the largest P2P lending platforms. Consistent with our hypotheses, we find that under platform-mandated posted prices, loans are funded with higher probability, but the preset interest rates are higher than borrowers' starting interest rates and contract interest rates in auctions. More important, all else equal, loans funded under posted prices are more likely to default, thereby undermining lenders' returns on investment and their surplus. 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.

Keywords: peer-to-peer lending; market mechanisms; auctions; posted prices; debt crowdfunding
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1. Introduction

In recent years, online peer-to-peer lending (P2P lending, also known as marketplace lending) has emerged as an appealing new channel of financing (Zhang and Liu 2012, Lin et al. 2013, Rigbi 2013, Iyer et al. 2016, Lin and Viswanathan 2016). Online P2P lending platforms allow individual lenders to aggregate their funds to finance loan requests from individuals and businesses. It is essentially a debt form of crowdfunding. By one estimate, in the year 2014 alone in the United States, P2P lending generated more than \$8.9 billion in loans and received more than \$1.32 billion in venture capital investments.[1] Investors, businesses, and regulators are all increasingly interested in this new business model. It is a prime example of how information and Internet technologies are transforming the finance industry.

P2P lending platforms are essentially online markets that match the 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 P2P lending, are auctions and posted prices. As their names suggest, auctions typically rely on the relative strength of the market participants (i.e., supply versus demand) to uncover the price, through an auction process; posted prices start with a predetermined price instead. P2P lending 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. Market mechanisms have the potential to affect the behavior of both sides of the market, the platform, and overall social welfare, and are 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 P2P lending, despite its potential impact on this nascent but burgeoning industry. The research question that we address in this paper, therefore, is the following: *How*

[1] http://cdn.crowdfundinsider.com/wp-content/uploads/2015/04/P2P-Lending-Infographic-RealtyShares-2014.jpg (last accessed August 24, 2016).

do these mechanisms compare in terms of their influence on market participant behaviors, transaction outcomes, and social welfare?

P2P lending is an ideal context to study the impact of market mechanisms. First, both types of mechanisms are used in P2P lending in different platforms across the globe. Despite some small variations, the primary features of these mechanisms are highly consistent on different platforms. Second, P2P lending features an unequivocal and universal metric for "price," i.e., interest rate of loans. Third, the quality, or ex post resolution of uncertainty associated with each loan, can be objectively measured when loans reach their maturity. Last but not least, we observe a unique regime change on an online P2P lending platform. Therefore, even though the impact of market mechanisms can be studied in different contexts, including product markets or other types of crowdfunding, P2P lending provides many unique advantages to investigate this research question.

We study the impact of the market mechanisms on loan transactional outcomes and also social welfare. To this end, we first propose an analytical model comparing a multiunit uniform-price auction against the posted-price mechanism in P2P lending. Our model predicts that the P2P lending 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. Loans will be funded with *higher* probability under the posted-price mechanism. 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.

Our empirical analysis employs detailed transactions data from Prosper.com, one of the leading P2P lending platforms in the United States. 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 auctions model and switched the entire website to a posted-price mechanism (Renton 2010).[2] 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.[3] 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, 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 (i.e., less herding). In addition, we find that the initial and contract interest rates under the posted-price mechanism are 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.

To better understand the consequences of market mechanisms, 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

[2] Renton (2010) provides evidence that this change was largely unexpected. Prosper.com's corporate blog about the regime change can be found at https://web.archive.org/web/20110312134825/http://blog.prosper.com/2010/12/30/exciting-new-enhancements-at-prosper/ (last accessed August 24, 2016). 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 Section 5.3.2.

[3] 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 different 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. We discuss more along these lines toward the end of the paper.

supply curve to derive lender 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 peer-to-peer lending as well as the broader literature on crowdfunding. Recent investigations include Zhang and Liu (2012), Burtch et al. (2013), Hahn and Lee (2013), Lin et al. (2013), Rigbi (2013), Kawai et al. (2014), Kim and Hann (2015), Iyer et al. (2016), and Lin and Viswanathan (2016). Given the global expansion of this industry, our study has important and timely implications not only for researchers and practitioners, but for policy makers as well. Since crowdfunding is essentially sourcing *funds* from the crowd, our study also contributes to the growing literature on crowdsourcing, such as Dellarocas et al. (2010), Hosanagar et al. (2010), Chen et al. (2014), 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 can be found in treasury auctions (Ausubel et al. 2014, Hortaçsu and McAdams 2010), initial public offerings (IPO) (Biais et al. 2002, Zhang 2009), and online product markets (Chen et al. 2007) such as eBay.com (Wang et al. 2008; Hammond 2010, 2013; Einav et al. 2016).[4]

2. Research Context

Since the inception of Zopa.com in 2005 in the United Kingdom, 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. As of 2014, there were over two million registered members (either as a borrower, a lender, or both) on Prosper.com. More than 100,000 personal loans, valued over USD 2.4 billion in total, had 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 three 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.

Before December 20, 2010, once the listing is posted with a specified expiration date (typically in seven 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. 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, which will apply to all lenders in that loan. In other words, the borrower sets the initial interest rate, and the auction "discovers" 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 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

[4] Einav et al. (2016), notably, document a trend by eBay.com sellers to gradually switching from auctions to posted prices. However, it is important to note that on eBay.com, market mechanism is an endogenous choice of sellers. In P2P lending, market mechanisms are imposed by the platform. There are many other important differences between these contexts, and between our study and theirs, which we will discuss at the end of this paper.

[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 (2016), for further details.

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

	Auctions	Posted prices
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

is the rate preset at the beginning. Table 1 summarizes the key difference between these two regimes.

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 these hypotheses using data from Prosper.com around the time of the regime change. After that, we examine the social welfare implications of this regime change.

Before we dive into the analytical model, it is 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 development.

3. A Model of Market Mechanisms

We now propose a model to compare the multiunit uniform-price auctions against platform-mandated posted prices. 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 *incentives* of key stakeholders including borrowers, lenders, and the platform. It allows a more formal process of hypothesis development and ensures that our hypotheses are based on general features of the market and stakeholder incentives, not peculiarities of the natural experiment that we 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), Sun (2012), and Lemmon and Ni (2014).

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 posted-price mechanisms (Chen et al. 2014). 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 preset 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 to 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, $n = 1, 2, \ldots, N$. 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 kth lowest value among N IID willingness-to-lend, and $k = 1, 2, \ldots, N$. 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 incur a nonnegative transaction cost, λ. It reflects the lenders' efforts to overcome uncertainties associated with the auction process, such as evaluating the borrower's creditworthiness, deciding whether the ongoing interest rate reflects borrower quality, observing the behavior of other investors (Zhang and Liu 2012), and accepting the risk 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) suggests 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 derive the borrower's payoff function, we notice that this is a personal loan market with borrowing and repayment obligations in a future date. 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:

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

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 lower 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 $E[W^{N:Q+1}+\lambda \mid W^{N:Q+1}+\lambda\le r]$ and r, respectively. Therefore, we can write the borrower's expected payoff as

$$\begin{aligned} E\pi_A = {} & \frac{Q\cdot[\tau - E[W^{N:Q+1}+\lambda \mid W^{N:Q+1}+\lambda\le r]-c]}{1+\tau} \\ & \cdot \Pr(W^{N:Q+1}+\lambda\le r) + \frac{Q\cdot(\tau-r-c)}{1+\tau} \\ & \cdot \Pr(W^{N:Q}+\lambda \ge r > W^{N:Q+1}+\lambda). \end{aligned}$$

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 as in Equation (1). 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 lower than the borrower's underlying maximum acceptable rate, $\tau - c$. This allows the borrower to secure a positive expected profit. 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.

[6] Recall that we assume the borrower's discount rate to be τ. We can interpret this 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. Hence, the borrower's reserve interest rate must satisfy $r<\tau$. Our results later confirm this observation.

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, we first consider a *hypothetical* setting where the borrower is able to choose the interest rate under posted prices. Note that this is, in fact, not possible on Prosper.com even after the regime change, but it merely provides a useful starting point for our analysis. This hypothetical setting is analogous to the model in Einav et al. (2016). More specifically, *if* the borrower could choose the fixed interest rate, his expected payoff can be written as

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

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 $\gamma(p) = p - \delta(p)(1+p)$; this 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 result in our hypothetical setting is an extension to Einav et al. (2016). 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.

In reality however, it is Prosper.com that determines the posted interest rates. The platform presets the interest rate p for a particular loan. The borrower's strategy is to pick a threshold or cutoff rate $\tilde{p}$. If p is lower than this cutoff, 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 the probability of full funding 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 preset interest rate can be shown to be $(Q \cdot (\tau - p - c)/(1+\tau)) \cdot \Pr(W^{N:Q} \leq \gamma(p))$, while rejecting the offer generates zero payoff. At the threshold, the borrower is indifferent between accepting and rejecting. That is, $(Q \cdot (\tau - p - c)/(1+\tau)) \cdot \Pr(W^{N:Q} \leq \gamma(p)) = 0$. 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 fixed fee, i.e., Prosper.com does not change it in the short run (consistent with what we observe for our study period). Then Prosper.com's expected profit is

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

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., $\tau - c$.

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 auctions, $\Pr(W^{N:Q} + \lambda \leq r^*)$, is strictly lower than

[7] This is a reasonable assumption since we interpret τ as the borrower's lowest interest rate from outside options. As a professional financial organization, Prosper.com has the credit information necessary to derive the interest rate that the borrower is able to obtain from other channels.

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

that with 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. Therefore, we summarize the following hypotheses from the model:

Hypothesis 1. *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. *Conditional on loans being funded, the contract interest rates under the posted-price mechanism are* higher *than those under the auction regime.*

Hypothesis 3. *The funding probability under the posted-price mechanism is* higher *than in auctions.*

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

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 on 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 in 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 data set 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 were 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

[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.

[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.

Table 2 Summary Statistics: All Listings

	All listings		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 *Years*	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
Number of observations	13,017		8,470		4,547			

Notes. 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/ (last accessed August 24, 2016).

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 increased after the regime change, and that the average asking interest rates and contract interest rates for funded loans both declined under posted prices, when we do not control for any covariates. We also find that half of the funded loans under posted-prices received full funding within 80 hours, compared to more than 160 hours in the auction regime; this is consistent with

[11] Prosper.com also extended listing durations from 7 to 14 days. As we will show later in Section 5.3.2, this is highly unlikely to be driving our findings.

Table 3 Summary Statistics: Funded Loans

	All listings		Auctions		Posted prices			
Variable	Mean	SD	Mean	SD	Mean	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	6,108.74	4,321.44	5,234.43	4,057.03	6,776.35	4,398.17	−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	6,035.19	661.71	4,283.06	844.65	7,087.08	−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	5,997.56	2,821.95	5,945.18	2,843.14	6,037.56	2,805.56	−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	16,409.10	34,784.77	16,615.13	33,808.10	16,251.77	35,518.38	0.35	0.64
Stated Monthly Income	5,533.68	12,454.72	5,040.51	4,108.85	5,910.26	16,136.82	−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
Number of observations	4,446		1,925		2,521			

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.

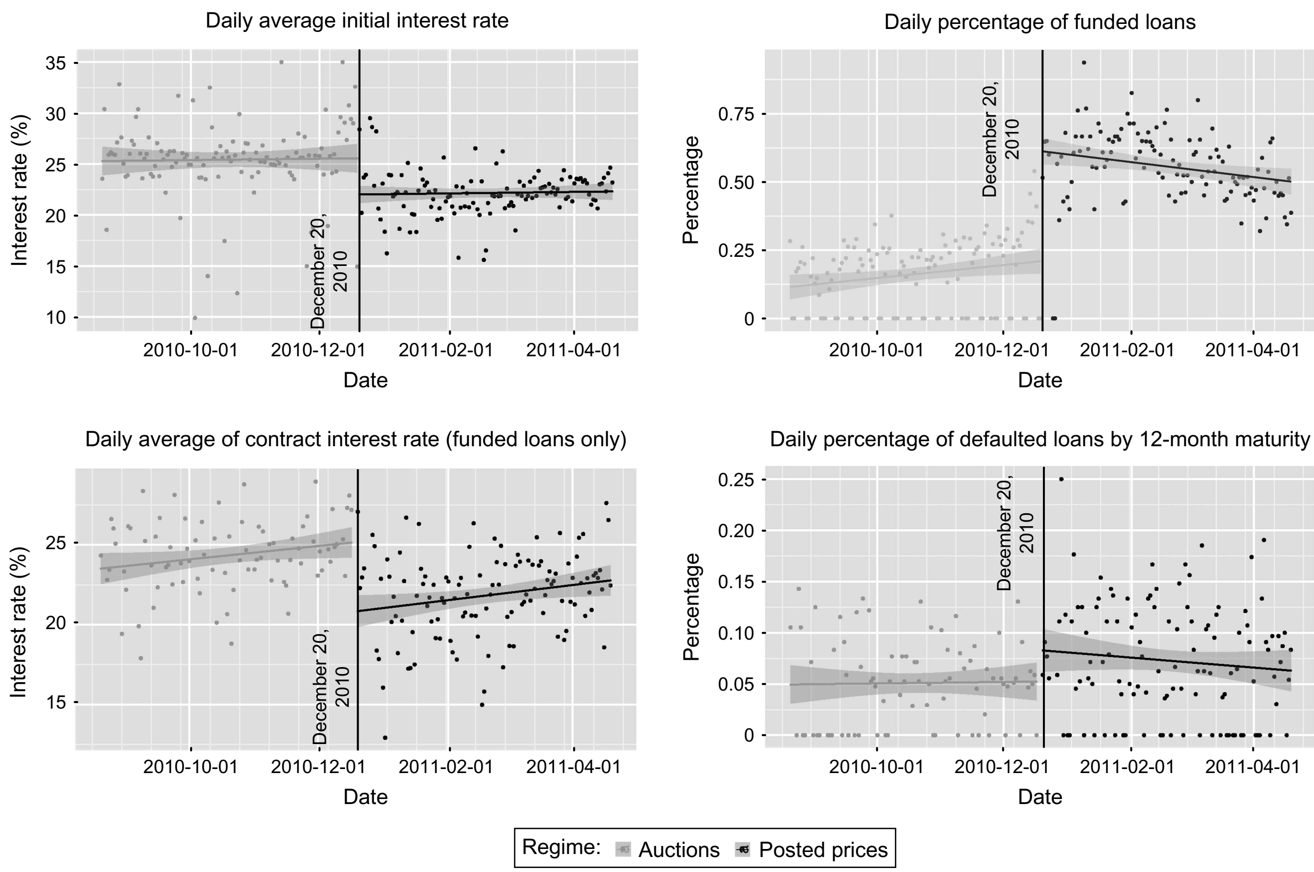
5. Empirical Analysis: Impact of Market Mechanism on Funding and Repayment

We now turn to the empirical tests. Our empirical tests consist of two major tasks. In this section we examine the impact of market mechanisms on transactional outcomes by testing the hypotheses discussed above, and on lenders' behaviors such as the amount and timing of bids as well as their herding behavior (Zhang and Liu 2012). In the next section we examine the impact of the market mechanism change on social welfare.

5.1. Empirical Strategy

Our analytical 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 paribus*. Further, the *contract* interest rates (for funded loans), funding probability, and default rate should all be higher under posted prices. Before we test these hypotheses, we notice that borrowers under posted

Figure 1 Daily Transaction Outcomes Before and After the Regime Change

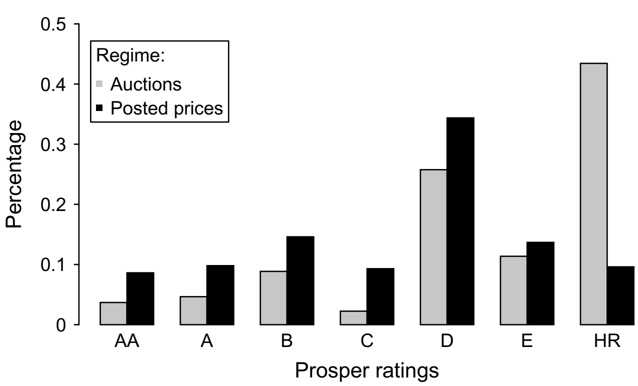


prices have better credit (see Tables 2 and 3 and Figure 2): The fraction of borrowers with better credits is significantly higher than before. We further notice that the drop in the number of posted listings (Table 2) is mainly due to the decrease in the number of high risk borrowers. Our empirical 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. We further control for the creditworthiness categories of borrowers as specified by Prosper.com. Prosper.com sets the interest rate for different borrowers based on their credit rating, the term of their loans, and the number of previous Prosper loans. For example, on September 26, 2011, borrowers at the "A" credit grade could have four possible interest rates. If they had one or more Prosper loans previously, their loans' interest rate would be 9.29% if they were requesting a one-year loan, or 11.29% if they were requesting a three-year loan. In contrast, if they had no prior Prosper loans, their interest rate would be 10.70% if they were requesting a one-year loan, versus 13.90% if they were requesting a three-year loan. There are 24 such categories as of that day across all credit grades.[12] We control for borrower creditworthiness categories in this manner as well.

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 treatment effect associated with the

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



[12] Screenshots of this pricing table can be viewed on Archive.org at https://web.archive.org/web/20110926231350/http://www.prosper.com/loans/rates-and-fees/.

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

	Matching estimates ($M=4$)							
Dep. var.:	*Initial Interest Rate*[a]		1(*Loan Funded*)		*Contract Interest Rate*		1(*Defaulted*)[b]	
	(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
Number of observations	13,017	13,017	13,017	13,017	4,446	4,446	4,443[c]	4,443

Notes. 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. 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).

[a]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.

[b]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.

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

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

market mechanism change using nearest-neighbor propensity score matching. First, we estimate the following probability of being in the posted-price regime (the treatment) given the set of covariates discussed above, using a logit regression,

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

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" 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) in 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 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) are highly consistent with our matching estimates.

Our empirical results lend support to our hypotheses about the comparisons of initial 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 the posted-price regime, 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 1993). Notice that had we not controlled for the interest rate categories, the results would have been the opposite.

Table 4 shows that all else equal, the funding probability under posted prices is on average more than 30% higher than under auctions. 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]

Furthermore, estimates in panel (3) of Table 4 show 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 loans were more likely to be

[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 evidence of such seasonality.

funded under posted prices, it came at a nontrivial cost for borrowers 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 we present the estimation results in panel (4) of 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 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.

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 lends 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.

Figure 3 compares 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 we estimate their models using listings from both regimes. Estimation results (Table 6) show

[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 show 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 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.

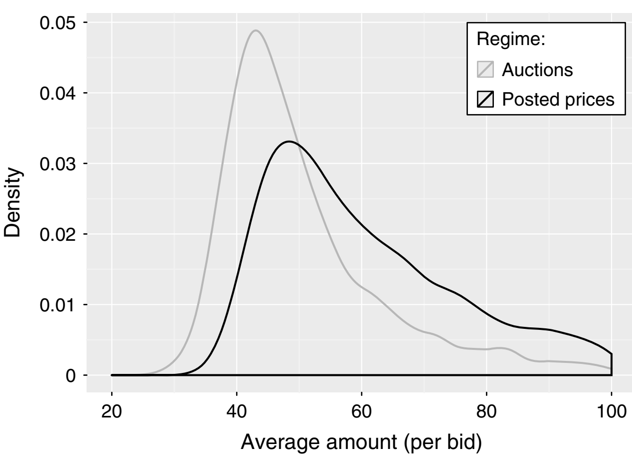
[15] In the main specification, we define a loan being defaulted if the status shows "more than four months late," "defaulted," or "charge-off." For robustness, we tried changing the definition of default to being late and beyond, one month late and beyond, two months late and beyond, or three months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

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

	Cox proportional hazard estimates				
	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
Number of observations	4,446	4,446	4,446	4,446	4,446

Notes. 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 four 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).
$^{**}p < 0.05$; $^{***}p < 0.01$.

Figure 3 **Distribution of Average Bid Amount Across Listings Before and After Regime Change**



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 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.

5.3. 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	
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 fixed effects	Yes	Yes
Day of listing fixed effects	Yes	Yes
Weekday fixed effects	Yes	Yes
Adjusted R^2	0.090	0.252
Number of observations	24,773	21,366

Notes. 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.
$^{*}p < 0.1$; $^{***}p < 0.01$.

5.3.1. Empirical Model Robustness.

Propensity Score Matching Sensitivity. The propensity score matching method that we use assumes selection on observables, so a common concern is that unobservables may be driving the difference between treatment and comparison groups. 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 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, we reestimate the regime change effects on interest rates, funding probability, and default rates using linear models. The specific equation we estimate is

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

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; $\mathbf{X}_{ir}$ are the control variables in Equation (4). The coefficient of interest is β_1, which captures the regime change effects.

We report estimation results using our main sample in the first, second, fourth, and sixth columns 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 the fifth column 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 the third and seventh columns of Table 7. Estimates of the regime effects are in the same direction as our matching estimates.

5.3.2. 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 was 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 seven 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 seven 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

Table 7 Comparisons of Transaction Outcomes Using Linear Regressions

	Transaction outcomes						
Dep. var.:	*Initial Interest Rate*	1(*Loan Funded*)		*Contract Interest Rate*		1(*Defaulted*)	
	OLS	OLS	Logit	OLS	Heckman[a]	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
Number of observations	13,017	13,017	13,017	4,446	13,017	4,443	4,443

Notes. This table displays estimation results of linear models for all transaction outcomes. For comparisons of funding probability and default rate at 18th-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.

[a]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 the two-step method.

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

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

	Cox proportional hazard estimates				
	Spec 1	Spec 2	Spec 3	Spec 4	Spec 5
exp(*Coef. of* 1(*Posted Prices*))	2.380*** (0.030)	2.796*** (0.035)	2.627*** (0.036)	2.632*** (0.036)	2.422*** (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
Number of observations	13,017	13,017	13,017	13,017	13,017

Notes. 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.
***$p < 0.01$.

fund even if we account for the funding duration difference.

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 could choose 3, 5, 7, or 10 days as the funding duration. Starting on April 15, 2008, the platform standardized durations for all listings to seven 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 three- or five-day durations prior to April 15, 2008, which were increased to seven 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.

5.3.3. 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 points, nonetheless we 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 one listing before the regime change. We repeat our matching estimations by including loan requests with at least 90% of these "old" lenders. Results are presented in Table 9 and are highly consistent with our main findings.

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 4 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.

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 negligible. This ratio is even higher for funded loans, with almost all funded

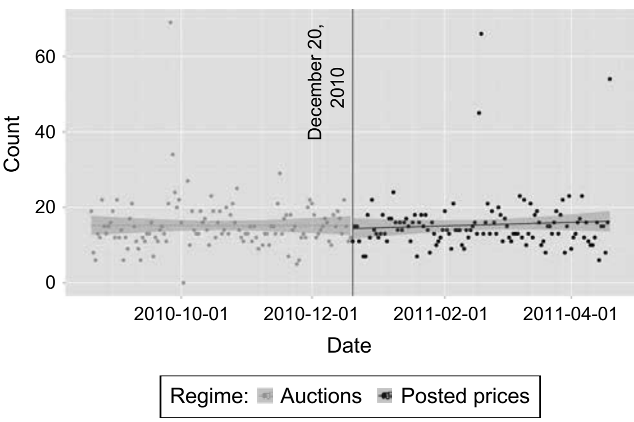
[16] Because of space constraints, we do not report the results here, but they are available from the authors upon request.

Table 9 **Matching Estimates of Regime Change Effect Considering Lender Compositions**

	Matching estimates ($M = 4$)			
Dep. var.:	*Initial Interest Rate*	1(*Loan Funded*)	*Contract Interest Rate*	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
Number of observations	12,047	12,047	3,943	3,940

Notes. Only loan requests with at least 90% of lenders that participated before the regime change are included. Similar results appear for other thresholds such as 70% and 80%.
$^{*}p < 0.1$; $^{***}p < 0.01$.

Figure 4 **Daily Number of Newly Registered Lenders Before and After the Regime Change**



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.

5.3.4. Alternative Explanation: Role of Soft Information? Research has shown that soft information or nonstandard information about borrowers, not available to traditional banks, can influence lender decisions in P2P lending (Iyer et al. 2016). If low quality borrowers are more likely to use soft information, and soft information is *more* likely to positively impact investor behavior under posted prices, then we will observe that borrowers are more likely to default under the posted-price regime, because bad borrowers are more likely to be funded but will not be able to repay.[17]

This, however, did not turn out to be a valid alternative explanation for our findings, because (1) after the regime change, among borrowers who use soft or nonstandard information, the proportion of high quality borrowers is, in fact, higher; and (2) we did not find evidence that the impact of soft or nonstandard information changes in a statistically significant way after the regime change. Evidence for the first point is presented in Figure 5, which shows that among borrowers with soft information, the proportion of higher credit grade borrowers is in fact *higher* after the regime change, regardless of which soft information variable we look at. Evidence for the second point comes from a formal statistical test, where we interact these soft or nonstandard information variables with the regime change dummy. The coefficient for the interaction term is positive for some variables and negative for others, but none is statistically significant, as shown in Figure 6, which illustrates the point estimates and 95% confidence intervals of these coefficients.[18]

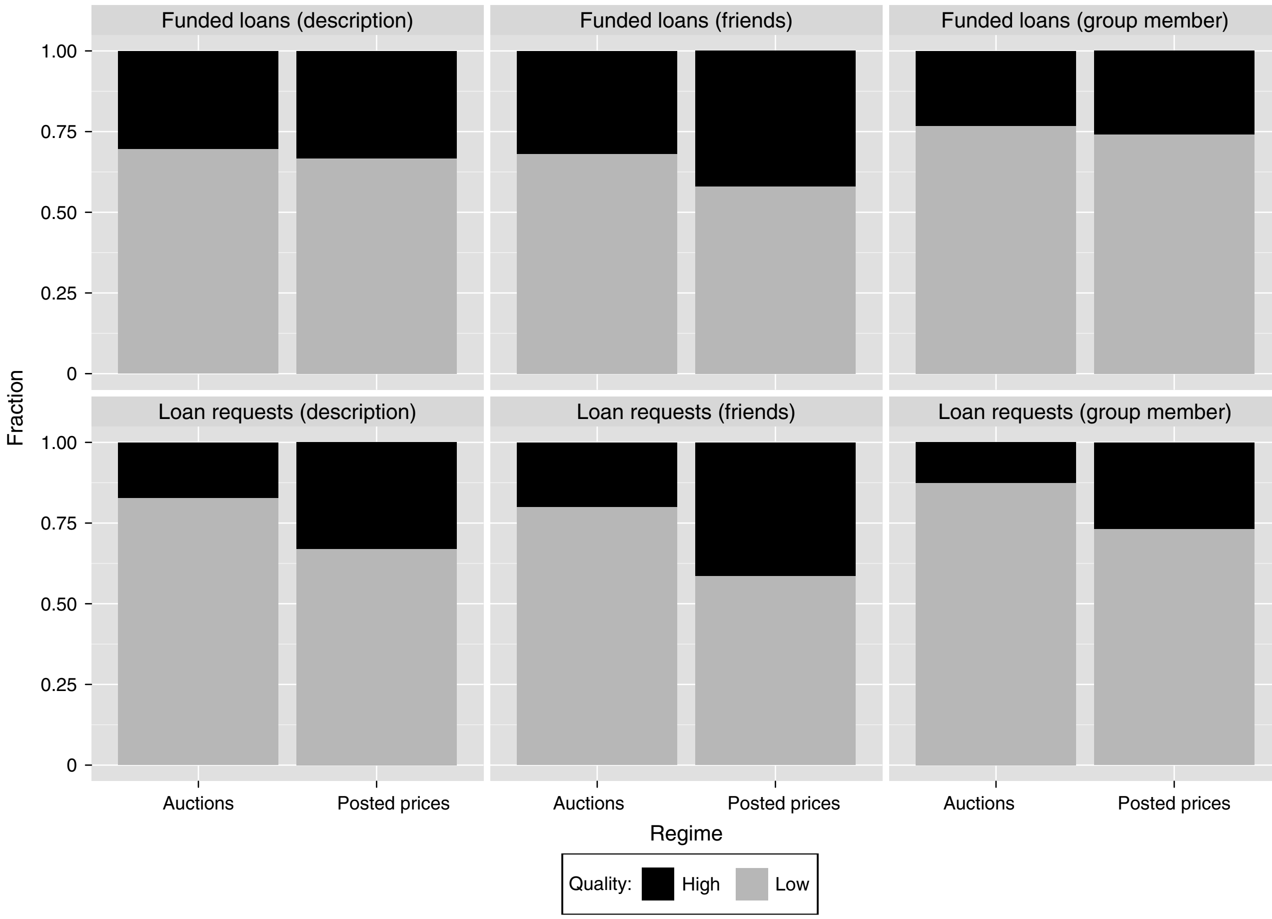
5.3.5. Alternative Samples.
Extended Sample. Another potential concern is the sample used in our estimations. Our main sample contains all listings posted four months immediately before and after the regime change. As an alternative, we compare loans that were generated four months before the regime 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.

"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

[17] We thank an anonymous reviewer for pointing us to the role of soft information.

[18] These coefficients are also not statistically significant when we use default likelihood as dependent variable.

Figure 5 **Distributions of Personal Loans (Funded or In Request) with "Soft Information"**



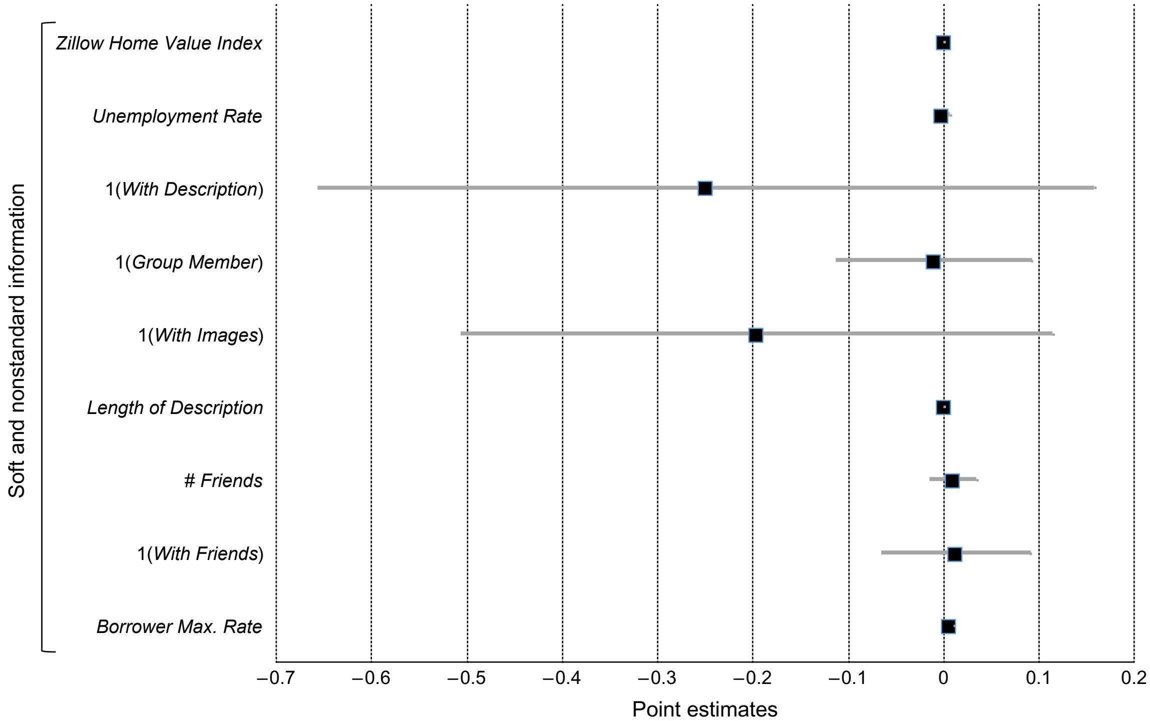
listings, and 40 of them were successfully funded. The interest rates of these loans were frozen at the time of the change, and the funding processes continued under the prevailing rates using the posted-price mechanism; they would be originated immediately when they receive 100% funding. In all previous 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 10 **Matching Estimates of the Regime Change Effects Using an Extended Sample**

	Matching estimates ($M = 4$)			
Dep. var.:	Initial *Interest Rate*	1(*Loan Funded*)	Contract *Interest Rate*	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
Number of observations	16,459	16,459	5,438	5,438

Note. In this table we compare loans that were generated four months before the regime change and those posted between April 20, 2011, and August 19, 2011.
***$p < 0.01$.

Figure 6 (Color online) Changes in the Effectiveness of Soft/Nonstandard Information on Funding Success



Notes. Each square represents the point estimate of the coefficient for the interaction term between that variable and a dummy for posted prices. Each grey line represents the 95% confidence interval of that estimate. If that line covers 0, it is not statistically significant.

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

	Matching estimates ($M = 4$)			
Dep. var.:	*Initial Interest Rate*	1(*Loan Funded*)	*Contract Interest Rate*	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
Number of observations	12,873	12,873	4,406	4,403

Note. We exclude "interim" loans that were still being funded at the time of the regime change.
*** $p < 0.01$.

6. Empirical Analysis: Impact of Market Mechanism on Social Welfare

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 understand which market mechanism generates higher overall social welfare.

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 the online appendix (available as supplemental material at http://dx.doi.org/10.1287/mnsc.2016.2531). Since the platform captures all borrowers surplus, borrowers' surplus should be decreasing, and the platform's surplus should be

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

	Matching estimates ($M = 4$)			
Dep. var.:	*ROI* (%)[a]		*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
Number of observations	4,443	4,443	4,446	4,446

Note. This table presents the nearest-neighbor propensity score matching estimates of the regime change effects on lender ROI and surplus.
[a]We examine the ROI by the 18th billing cycle (or month) since origination. Similar results hold for 6th or 12th billing cycle.
$^{***}p < 0.01$.

increasing.[19] 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 a tradeoff between higher nominal contract interest rates and higher default likelihood. Our analysis in the online appendix illustrates conditions under which auctions can generate *higher* social welfare than posted prices.

To further determine the net total surplus change due to the regime 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 18th 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, we first 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[20] of the supply function, $W = \alpha \cdot Q^{\gamma}$. We 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

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

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

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 using the calculated lender surplus on a loan as the dependent variable. 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, 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.

7. Discussions and Conclusions

7.1. Summary of Results

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, this choice is especially critical but not well understood. For market designers, platform owners, and policy makers, 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 United States both use posted prices, many peer-to-peer lending platforms in other countries still use auctions. More important, there is little systematic empirical evidence in favor of a particular mechanism, and the popularity of posted-price mechanisms per se does not guarantee its efficiency or superiority.

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 support 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. Most 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: All else equal, loans are 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 suggest that the regime change actually resulted in a net loss in total social welfare. While the traditional "crowd"-based auctions may be slower to fund loans, its long-term welfare impact 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.

7.2. Contributions to Literature

Our paper contributes to the growing literature in online peer-to-peer lending by systematically documenting intended and unintended (and previously unknown) consequences of market mechanism changes. We exploit an exogenously imposed regime change to study the impact of market mechanisms on transactional outcomes such as funding probabilities and repayment likelihood, and on overall social welfare. Furthermore, by comparing the impact of auctions against posted prices, our paper also contributes to the long-standing broader literature on market mechanisms. A notable paper in that literature is Einav et al. (2016), which documents an interesting trend that eBay.com sellers increasingly prefer posted prices to auctions. However, as shown in Table 13, our paper is different from Einav et al. (2016) not just in the context that we study, but also in terms of the goal, method and findings.

Table 13 A Comparison of This Study vs. Einav et al. (2016)

	Current study	Einav et al. (2016)
Context difference		
Who decides on which mechanism to use?	The platform; borrowers cannot opt out	Each individual seller; sellers are not obliged to use posted prices
Who sets the price under posted prices?	The platform	Each individual seller
How did the mechanism change take place?	Instantaneous (overnight) and exogenous to borrowers and lenders	Gradual and endogenously chosen by each seller
Nature of the market	A market for personal loans	A market for physical products
Paper difference		
Research goal	What impact market mechanisms have on individual behaviors, transactional outcomes, and social welfare	What drives sellers to increasingly prefer fixed prices to auctions
Identification	The overnight switch in mechanisms	"Seller experiments," i.e., many sellers sell the same items using different mechanisms
Opposite findings	Under posted prices, interest rate is higher, and probability of funding is higher	Under posted prices, price is higher (corresponding to lower interest rate in loan settings), and probability of sale is lower

7.3. Generality of Findings

While our main analysis is based on data from Prosper.com around the time of a natural experiment that occurred in 2010, the findings nonetheless should still be relevant today and should generalize well to other peer-to-peer lending platforms. First, from a temporal point of view, Prosper.com is still similar to what it was around the time of the regime change. When we examine data from 2013 (the most recent time when Prosper.com makes its detailed data publicly available), the most popular three categories of loan requests have always been debt consolidation, home improvement, and businesses. In addition, the relative forces between the demand and supply of funds are highly comparable as well: We find that the ratio between borrower requested funds and investor investments, and the ratio between number of lenders and the number of loan requests, are both statistically indistinguishable between the time of the natural experiment and 2013. Second, the incentives of all major stakeholders (platform, borrower, and lender) that we formally modeled are consistent with most, if not all, peer-to-peer lending platforms that we are aware of. In addition, the posted-price mechanism on Prosper.com is essentially the same as that implemented on its main rival, LendingClub.com, and other platforms outside the United States. The auction mechanism that Prosper.com previously used is still widely seen in many peer-to-peer lending platforms around the globe. For these reasons, our findings still have important relevance today and for other peer-to-peer lending platforms.

7.4. Future Research

Our study is situated in the context of P2P lending, a debt form of crowdfunding. Yet, the issue of market mechanism is a fundamental one in other types of crowdfunding as well, and this can be a fertile direction for future research. Even though the concept of initial interest rates may manifest itself differently in 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 all 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, crucially depends 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 strong network effects. Linking market mechanisms to interplatform competitions, therefore, is also an interesting area of future empirical research. 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 or firm valuation), a revenue model that takes into account long-term performance (e.g., linking platform revenue to debt repayment, rewards shipment, or venture success), or further innovations (e.g., other market mechanisms).

Supplemental Material

Supplemental material to this paper is available at http://dx.doi.org/10.1287/mnsc.2016.2531.

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