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**Borrowers in Search of Feedback: Evidence from Consumer  
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# Borrowers in Search of Feedback: Evidence from Consumer Credit Markets <sup>\*†</sup>

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## Abstract

We study recent technological innovation in credit markets and document their role in providing information to households. We show that households value the ability to learn detailed information about their cost of credit. This function is most valued by less creditworthy households with less experience in credit markets. To measure the demand for information provision we exploit a quasi-natural experiment in an online consumer credit market. A large lending platform unexpectedly switched from pricing loans through an auction mechanism to centralized pricing determined by broad credit grade. This change resulted in an instant decrease in the amount of tailored feedback available to market participants. We find that less experienced households immediately and disproportionately exit the market and the response is concentrated among higher risk households. We rule out alternative explanations such as changes in access to credit, borrower risk profiles, and interest rate levels. Our findings point to a potentially important role for financial innovation: enabling less experienced households to more easily learn about their credit market options.

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<sup>†</sup>The views expressed are solely the responsibility of the authors and should not be interpreted as reflecting the views of the Board of Governors of the Federal Reserve System or of anyone else associated with the Federal Reserve System.

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# 1 Introduction

Recent advances in technology have raised the question of how technological and financial innovation affect household finance. An important aspect of this innovation has been to facilitate households' access to credit markets (Campbell, 2016). Most discussion of this trend has centered around its effect on credit extension to households. However, these markets also allow borrowers to learn about their credit costs. In particular, households can use credit markets to obtain individualized feedback about the interest rates at which they can borrow. We define feedback as any information that may allow borrowers to learn about their credit market options. This access to information is especially valuable for households whose prior experience in credit markets is more limited. In this paper we provide empirical evidence that less experienced households indeed place more value on access to feedback and that recent innovation can help meet that demand.

Information about the cost of credit has long been highlighted as an important factor in households' credit decisions. Households that collect more credit offers and learn more about their costs of credit are able to borrow at lower rates (Stango and Zinman, 2016). As a result, the search costs of finding these offers is considered an important feature of credit markets (Ausubel, 1991; Calem and Mester, 1995). There is broad consensus that these costs have decreased over the last few decades. For one, the introduction of the internet allowed consumers to go online and compare multiple credit card offers. In other words, households could more easily access feedback in credit markets. However, this change occurred gradually and therefore it is difficult to measure its effects.

A more recent wave of technological innovation has further expanded individuals' ability to learn about their credit markets options. New credit platforms provide highly individualized interest rate offers to prospective borrowers. These platforms communicate credible rates, in contrast to sometimes misleading quotes from websites that aggregate loan offers. These credible, tailored rates may allow borrowers to more quickly learn about their creditworthiness and cost of credit. We use an exogenous change in the amount of information

provided by one such platform to identify how households respond to changes in barriers to information.

We focus on a particular consumer credit market, the online peer-to-peer lending platform, Prosper. This platform hosts an online marketplace where individual borrowers can publicly list a loan application, which individual lenders can then choose to fund. This offers an attractive setting to study households responses, for two main reasons. First, it allows us to observe the universe of loan applicants on the platform. Using Prosper’s SEC filings, we collect detailed data on features of all listings and funded loans, as well as borrowers’ characteristics. This stands in contrast to most credit market settings, where only successfully funded loans are observed. Consequently, we are able to focus on households’ decisions to participate in the credit market. Second, the users of Prosper’s platform are made up of a population that is of particular interest to us. Many prospective borrowers are applying for loans to consolidate existing high interest rate debt, usually on credit cards. It is exactly these households that could most benefit from better understanding their individual cost of credit. It is therefore important to determine whether they indeed value access to this information.

We exploit a natural experiment in Prosper’s structure to measure an exogenous change in the type of information available to borrowers. As Prosper grew, it experimented with various features of the listing environment and with loan contracts. These changes were unexpected and unprompted, thus creating several natural experiments that allow us to draw causal inference. In our main experiment, Prosper unexpectedly changed the mechanism by which interest rates were assigned to loans. Originally interest rates were assigned through an auction process. Prospective borrowers would request an interest rate which could then be bid down by lenders. This setting provided households with an highly individualized feedback on their interest rates. In December 2010, the platform unexpectedly switched from auction pricing of loans to centralized rate assignment by credit grade. After the change, all borrowers in a given credit grade were assigned the same interest rate. Accordingly,

the amount of information households could learn from the platform instantly decreased and became less individualized. This constituted an exogenous decrease in the amount of feedback available to borrowers. We similarly use a later, different experiment to establish the robustness of our results.

To identify a causal effect we focus on a narrow window around the date on which the auction mechanism was abandoned. Immediately following the elimination of the auction, households with shorter credit histories chose to leave the platform. Moreover, the effect is driven by the higher risk, less creditworthy borrowers on the platform. Among these borrowers, there is a 25% standard deviation increase in credit experience. We show that there are no concurrent changes in other credit characteristics or in loan performance, verifying that this effect is unique to credit experience. Our findings suggest that online credit markets are valuable in providing feedback to households, above and beyond their function as credit providers, especially for less experienced households.

So far we have highlighted that once the auction is eliminated, borrowers no longer receive tailored individualized interest rates. While this changes the feedback they receive, it also directly affects the interest rate levels assigned to them. In a series of tests we rule out the possibility that the observed effects are driven by the changing interest rates. First we show that less experienced borrowers do not receive more favorable pricing than other borrowers under the auction mechanism. This could occur if they were better able to convey soft information or fish for advantageous rates, and would lead them to prefer the auction setting. Instead, we document that their listing behavior in auctions is more consistent with learning. They submit lower initial rates but in repeat listings they adjust their starting rates by more than other borrowers.

We next demonstrate that our results are not driven by contemporaneous changes or trends. The auction elimination is accompanied by a level increase in interest rates. In order to disentangle the effect of this shift we study a second natural experiment. A unilateral interest rate decrease was instituted within a month of the shift away from auction pricing,

yet it was not accompanied by a change in the experience length of prospective borrowers. To rule out unobserved industry trends, we examine Lending Club, Prosper’s main competitor. We find no concurrent changes in Lending Club’s participant pool. Finally, we rule out seasonal effect by demonstrating that no similar changes occurred exactly one year prior to the auction change.

Our paper is closely related to the growing literature on household and consumer finance (Campbell, 2006). A number of papers have noted that the decision to take on expensive debt is correlated with household characteristics such as financial literacy (Lusardi and Mitchell, 2014; Lusardi and Tufano, 2009), cognitive abilities (Agarwal and Mazumder, 2013; Stango and Zinman, 2009), and age (Agarwal et al., 2009). Others have shown that these behaviors can be lessened through disclosure and framing (Bertrand and Morse, 2011; Stango and Zinman, 2011), subsidies (Cole et al., 2011), or simplification (Drexler et al., 2014). Research on the exact choice inefficiencies that contribute to overpayment for debt highlight the willingness to search across credit contracts (Stango and Zinman, 2016; Zinman, 2015). However, to the best of our knowledge, no one has documented market attributes that may compel households to engage in search for feedback.

Our paper is also part of the emerging literature on online marketplaces.<sup>1</sup> Most papers have focused on lenders’ pricing decisions in these markets and the types of information that they incorporate (Iyer et al., 2016; Ravina, 2012; Duarte et al., 2012; Pope and Sydnor, 2011; Lin et al., 2013; Freedman and Jin, 2014; Hildebrand et al., Forthcoming; Miller, 2015). Hertzberg et al. (2016) studies borrowers’ choices in online markets but focuses on adverse selection on loan maturity. Related to our focus on auctions, Einav et al. (2016) examine auction theory in the context of eBay. Most relevant for our paper, Wei and Lin (Forthcoming) use Prosper’s elimination of auctions to test a model of auction pricing. However, none of these papers study the role that auctions play in providing individualized

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<sup>1</sup>See Morse (2015) for a more comprehensive survey of this literature. See Moritz and Block (2016) for a survey of literature on crowdfunding more broadly.

feedback or address their effects on borrowers’ participation in credit markets.<sup>2</sup>

By focusing on borrowers’ decisions to participate in credit markets, we are able to uncover a novel facet of borrower demand. We document that households value the role of credit markets as information providers. Due to the nature of our quasi-natural experiment we focus specifically on the provision of highly individualized feedback. However, we believe that our results are more broadly applicable to increases in information provision. This is especially valuable for less experienced households, who are able to easily learn about their credit market options. We also demonstrate how this demand can be met by new financial marketplaces. Our results may be of particular interest to policymakers who want to encourage learning among less experienced and less creditworthy populations.

The remainder of the paper is organized as follows: Section 2 provides a description of the institutional setting and our dataset. In section 3 we explain our empirical methodology and section 4 presents our results. Section 5 concludes the paper.

## 2 Data and Institutional Setting

### 2.1 Institutional Environment

In this paper we exploit a quasi-natural experiment by the online peer-to-peer lending marketplace Prosper. Peer-to-peer marketplaces provide an online setting in which individual lenders and individual borrowers can be matched.<sup>3</sup> These marketplaces have risen in prominence as the market for online lending has grown tremendously over the past decade. Prosper launched in 2006 as the first peer-to-peer lending marketplace in the US and was followed shortly by Lending Club in 2007. The pace of online lending is expected to grow even fur-

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<sup>2</sup>After writing this draft we were made aware that Meyer (2014) also studies this change in an unpublished PhD thesis. Similar to Wei and Lin (Forthcoming) she focuses on loan outcomes after controlling for observable characteristics, rather than studying changes in the pool of borrowers.

<sup>3</sup>Although these markets initially attracted individual lenders, the investor base has expanded and currently includes institutional investors, hedge funds, and financial institutions. However, during the time period examined in this paper the majority of investors were individuals.

ther, with US Department of Treasury (2016) estimating 90 billion dollars in loan origination volume by 2020.

The loans issued by Prosper are all personal, unsecured, fully amortizing, fixed-rate loans with no prepayment penalty. These are similar to personal loans traditionally provided by banks. The rising popularity of online marketplaces within the personal loan market can best be understood within the context of the financial crisis. In the late 2000s, consumers lost access to forms of credit such as home equity lines (HELOCs) as banks became less willing to issue consumer loans.<sup>4</sup> At the same time interest rates fell, making the refinance of higher rate personal debt more attractive. As a result, borrowers increasingly turned to online marketplace lenders, which predominantly operate in the unsecured consumer credit market (US Department of Treasury, 2016). These lenders were able to offer the additional benefits of speed and convenience. The personal loan market has since grown and so-called “FinTech” lenders have grown ever more quickly, becoming a leading originator in this market (Cocheo, 2016).

The focus of our paper is on the earlier years of online lending, 2010-2011. At that time Prosper was one of the only online lenders operating in the US and the only one using the auction pricing system. Below, we describe this marketplace in detail, including the auction pricing system and its eventual elimination. The loans offered range from a minimum of \$1,000 to a maximum of \$25,000, and at the time studied generally had three-year maturities.<sup>5</sup> If a prospective borrower wants to apply for such a loan, they have to go to the Prosper website and complete a loan application. Prosper then obtains the prospective borrower’s credit report and uses that, along with data supplied by the borrower, to assign the listing a credit grade. The grade is determined by a proprietary risk model that incorporated Prosper’s data on the historical performance of similar borrowers. There are seven possible credit grades, with each corresponding to a different estimated average annualized loss rate

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<sup>4</sup>Based on time series data from the Senior Loan Officer Opinion Survey on Bank Lending Practices conducted by the Federal Reserve Board of Governors (Senior Loan Officer Opinion Survey on Bank Lending Practices , SLOOS)

<sup>5</sup>Additional maturity options were introduced later.



range.<sup>6</sup>

Once a prospective borrower has been assigned a credit grade, they can post their listing on the platform for potential lenders to view. In addition to the credit grade, each listing also displays the intended use of the loan, a short description, summary information from the borrower’s credit report, and self-reported employment data.<sup>7</sup> Potential lenders can then review all of the listings on the platform and make a commitment of at least \$25 towards any listing they wish to help fund. These commitments are technically commitments to purchase a promissory note from Prosper, where payment on the note is dependent on the payments Prosper receives from the borrower. Prosper’s partner bank, WebBank, originates the loan to the borrower and then sells it to Prosper. At the same time, Prosper sells a note to each lender who committed to fund the loan in the principal amount of that commitment. Prosper itself does not fund any loans, but it services them and earns revenue through a servicing fee and an origination fee.<sup>8</sup>

All of the above aspects of the marketplace remained constant under both auction rate-setting and centralized rate-setting. The one aspect that changed was the manner in which the interest rate was assigned. Under the auction regime, borrowers included in their listings the maximum interest rate they would be willing to pay – i.e., their reservation price. These rates were capped at 36% and were subject to a minimum interest rate based on the listing’s credit grade. Lenders would then bid on a listing by entering both a minimum acceptable yield and the amount they wished to invest in the listing. At the end of the auction bidding period, a listing would be funded if it had received aggregate purchase commitments at least equal to the full amount of the requested loan. Then the interest rate of the loan would be

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<sup>6</sup>The ratings are, from best to worst: AA, A, B, C, D, E, and HR. HR which stand for “high risk” is the lowest rating category. Prosper dropped listings in this category from the platform during parts of our sample period so we exclude them from our analysis.

<sup>7</sup>In the past borrowers were able to also include pictures of themselves, but did not do so at the time studied.

<sup>8</sup>The servicing fee is paid by the lenders at an annualized rate of 1%.The origination fee is paid by the borrowers out of the proceeds of the loan at the time of funding, and it differs across Prosper rating categories.

determined by the minimum yield acceptable to all the winning bidders on the loan.<sup>9</sup>

This method of interest rate assignment was suddenly and unexpectedly retired on December 19, 2010. Prosper subsequently switched to a posted price mechanism in which each listing was automatically assigned an interest rate prior to being listed. This interest rate was based only on the listing's credit grade and whether the prospective borrower had previously received any loans through Prosper. After observing the assigned interest rate, borrowers could decide whether to post their listing on the platform. If posted, lenders could still decide whether to commit any funds, and how much, but could not weigh in on the rate. Once a listing received committed funds totaling the requested loan amount, the loan was successfully funded.<sup>10</sup> As in the auction setting, if a listing is not successfully funded by the end of the bidding period, the listing is terminated and no loan is originated.<sup>11</sup> It is important to note that after the retirement of the auction a potential borrower knew their final interest rate prior to posting the listing on the platform and this interest rate was not tailored to the individual. This stands in contrast to the auction mechanism, where the borrower learned about their highly individualized interest rate over the course of the auction.

The stated impetus for the abandonment of the auction was that Prosper wanted to move to a simpler, more user-friendly platform. Our understanding of the policy change, from reading corporate announcements and blog posts, was that the simpler process would save time for lenders by allowing them to deploy funds with less hassle.<sup>12</sup> Thus the switch was driven not by particular recent events but by a broader desire to simplify the loan allocation

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<sup>9</sup>For a more detail description of the auction process see Prosper's prospectus filed with the SEC on July 26, 2010 <https://www.sec.gov/Archives/edgar/data/1416265/000141626510000317/prosperprosupp7d26d10.htm>

<sup>10</sup>In this setting Prosper made it possible to obtain a loan that was partially, rather than fully, funded. However, very few borrowers chose to take advantage of this possibility. In the first month of availability, zero borrowers chose to get a partially funded loan.

<sup>11</sup>The bidding period was 7 days under the auction mechanism but changed to 14 days under the posted price mechanism. However, loans are actually funded more quickly after the change because there is no need to wait for an auction to complete

<sup>12</sup>On December 30, 2010 the following was posted on Prosper's website: "The biggest change is that we have eliminated the auction for all new loan listings - from now on listings will have pre-set interest rates. While many lenders enjoyed the auction system conceptually, we heard consistent feedback that in practice, auctions made the deployment of funds more time consuming with little gain in lender returns," according to Chris Larsen, Prosper CEO.

process. The elimination of the auction also has the advantage of being unanticipated. Early in the week of December 13, 2010, rumors that auction might be scrapped began to circulate. This was confirmed on December 16, 2010 with a message to borrowers arriving at the website. At that point borrowers were no longer allowed to set their reservation rate but had to use rates assigned by Prosper. However, these rates could still be bid down by potential lenders through an auction mechanism in the following days. On December 19th, 2010, the auction mechanism was completely retired from the platform.<sup>13</sup> Thus this change in rate assignment was unprompted, unexpected, and serves as an appropriate natural experiment.

## 2.2 Data

We hypothesize that following the experimental elimination of the auction there will be a change in the types of borrowers that choose to list loans on the Prosper platform. To test this empirically, we need data on all prospective borrowers choosing to list on the platform, not just originated loans. We are able to collect this data through the Securities and Exchange Commission’s (SEC) online EDGAR platform. Because Prosper issues notes to the public, it is required to file prospectuses for all these notes with the SEC, which include information on both listings and funded loans. We collect listing and loan-level data from June 2010 through June 2011, roughly six months before and after the change in rate setting. Our data include the date that the listing or loan was filed with the SEC, as well as all borrower and loan characteristics that were available to the lender.<sup>14</sup> We then supplement this data with performance metrics publicly distributed by Prosper. These are measured as of the end of 2014, after the maturity dates of all the loans in our sample.

Within the sample of all listings, there are some important dimensions on which listings and borrowers may differ. When possible, we use these dimensions to compare the effects of

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<sup>13</sup><http://www.lendacademy.com/prosper-com-ending-their-auction-process-dec-19th/>

<sup>14</sup>The filing date is often the same as the date on which the listing was posted to Prosper. However, if there are too few listings on a certain date, such as on weekends, they will be combined with the subsequent listing date to form one filing date. Generally these correspond to business days in our sample.

the auction change on different groups of potential borrowers. However, in some cases there are not enough observations to conduct meaningful analysis and so we restrict our sample to listings for roughly comparable loans. In the time period we study, 92% of listings are for 3-year loans with another 6% for 5-year loans and the remaining 2% for 1-year loans. To ensure that we do not compare loans with different maturities to one another, we focus only on 3-year loans in this paper.<sup>15</sup>

Potential borrowers can also be broadly divided into first-time and seasoned borrowers. Seventy-eight percent of listings are from borrowers that have not previously taken out a loan on Prosper. In this paper we mostly focus on this set of borrowers. The other 22% are seasoned borrowers who obtained at least one loan on the platform in the past. This distinction between first-time and seasoned borrowers is an important one to Prosper. When rates are centrally assigned, they depend solely on credit grade and whether the borrower is seasoned. More importantly for our analysis, these borrowers are likely to consider different factors when they choose to list on Prosper. Seasoned borrowers may find it much more convenient to use a platform they already have experience with and are therefore less likely to leave Prosper. Moreover, these borrowers have already used the marketplace to determine an interest rate at which they can be successfully funded. Therefore, they may have less to learn from repeated interactions with lenders than first-time borrowers. We later return to seasoned borrowers separately and show that they do indeed react differently than others.

One of the main advantages of our dataset is the ability to see both the unfunded and funded listings submitted to the marketplace. We can then compare all listings to those that succeed and lead to loans. Table 1 summarizes all the listings in our dataset and Table 2 summarizes the originated loans. Listings and loans are summarized as a whole and then separately for lower and higher risk groups. We define lower risk as Prosper credit grades AA through C, which make up 40.5% of all listings and 43.7% of all loans. Higher risk listings are defined as those with a credit grade of D or E. Overall, we have a sample of 10,365

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<sup>15</sup>This exclusion does not change any of our results.

individual listings out of which 4,014 loans were funded. The most populated credit grade for listings is D, with 38% of the listings. The second most populated is E, with 21% of the listings.<sup>16</sup>

The start rate displayed for listings is the reservation rate chosen by the borrowers in the auction regime. In the posted rate regime, this is simply defined as the rate assigned by Prosper. The average rate posted is 21.5% but it is 13.2% for lower risk loans and 27.1% for higher risk loans. The average listing requests roughly \$7,000 and 38.7% of these get funded. Lower risk listings are for lower rates, larger loan amounts and have a greater probability of being funded. Although it is clear that the higher risk borrowers are relatively more risky, in reality all of these borrowers are prime and near-prime consumers. Indeed, Prosper does not accept applications from sub-prime borrowers. Approximate FICO scores are reported in Table 1, estimated as the mid-point of the 20 point FICO range that is reported for every borrower. The average approximate FICO score is 762 for lower risk borrowers but still high at 700 for higher risk borrowers.

At first glance, the interest rates listed may seem high given the risk profiles of these borrowers. Yet around this time the average interest rate for unsecured personal loans was approximately 15% and prime and near-prime borrowers make up a significant portion of this market.<sup>17</sup> The pool of borrowers using online markets tends to be riskier than those using banks, partially accounting for the higher rates on Prosper (Boyle and Becker, 2015). Consumers are also likely to accept a higher interest rate in return for the increased convenience and speed of online borrowing. An additional advantage is that Prosper's credit report listing on Prosper results in a soft credit report inquiry to as opposed to applying for a credit card or bank loans which generate a hard credit report inquiry which could worsen a borrower's credit score.

To better understand the high rates on these listings, it is useful to consider the characteristics of these borrowers and their reasons for taking out these loans. As shown at

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<sup>16</sup>Grade AA makes up 8%, A is 12%, B is 13%, and C is 9%

<sup>17</sup>This rate is for two-year loans, from a Bankrate weekly survey of banks and thrifts.

the bottom of the table, 44.6% of these loans would be for debt consolidation, and this is consistent across lower and higher risk listings. The three other common categories – home improvement, business, and auto loans – are much less popular.<sup>18</sup> By reading through listing descriptions and titles we found that, more specifically, these loans often aim to consolidate expensive credit card debt. Thus the pool of borrowers is skewed towards the types of households that have amassed credit card debt at high interest rates. These households have therefore not been prompt payers of credit card balances and may be less likely to repay unsecured loans than observably similar households.

Observable characteristics further suggest that the pool of borrowers is not representative of typical prime or near-prime borrowers. Rather, it is a pool of borrowers that have heavily utilized available sources of revolving credit. The average length of credit experience, measured as the number of years since the borrower’s first credit line was opened, is 16.4. In other words, if borrowers get their first credit card at 18 the average age in this sample would be a relatively young 34 years old. Yet credit card usage is already quite high. The average revolving balance, measured as the total outstanding balance on open credit cards or accounts, is \$21,700. The average prospective borrower utilizes 47.7% of the credit limit on their cards and has eight open credit lines. These statistics offer some evidence as to why these borrowers are choosing to use Prosper rather than borrow on additional credit cards. With a large number of existing credit lines, it becomes more difficult for them to open new cards. Note that even though our sample is not representative of consumers in the broader credit market, it captures a population that is of great interest to policy-makers. Most notably the CARD Act of 2009 aims to protect exactly those consumers that tend to accumulate high levels of credit card debt. It is therefore important to understand how this population reacts to recent financial innovation and the provision of tailored feedback.

In Table 2 we verify that these characteristics are broadly similar for those listings that are successfully funded. There are 4,014 successfully funded loans. The end rate is the rate at

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<sup>18</sup>Another 2% are for student use and about 25% are classified by the borrower as “other”.

which the loans are originated. Although loan amounts are slightly smaller for funded loans, at around \$6,000, the trends in credit characteristics are consistent with those described for all listings. For these loans we can also track their performance to better understand the risk that these borrowers represent. At the bottom of the table are indicators for whether the loan was charged off or defaulted. Prosper considers a loan charged off if it reaches 121 days past due. At this point, the entire loan balance becomes collectible in full and the borrower no longer has the opportunity to bring the loan current. Fourteen percent of all loans are charged off, with a much higher 19.7% for higher risk borrowers and a lower 6.9% for lower risk. A loan is considered defaulted when the borrower is delinquent and has filed bankruptcy or insolvency proceedings. Even using this conservative definition, 6.8% of loans default. These high rates of non-payment line up with the high interest rates charged on these loans.

Finally, we can directly measure the amount of feedback that borrowers receive in the form of interest rate bids from lenders. The average funded loan receives funds from 112 lenders, underscoring the role of Prosper auctions as an aggregator and conveyor of lender opinions. So far we have noted that average rates are higher for more risky borrowers but we have not studied the rate distribution. Yet this is an important component of a borrower's decision to participate in the marketplace. Lender feedback is likely to be more important to a borrower that has more to gain from learning their specific interest rate. In Figure 2 we show the listed and funded rates under auction pricing, by credit grade. As the credit grade increases, borrowers face an increase in the left tail of funded interest rates. Therefore borrowers in higher risk credit grades have more potential upside from participating in the auction process – they may learn they are less risky than average. For this reason we will focus separately on higher and lower risk borrowers in our empirical analysis.

### 3 Empirical Setting

To study the effect of the auction mechanism on borrower participation in the credit market, we exploit the natural experiment described earlier. As discussed in section 2.1, the elimination of the auction was an unanticipated change, unmotivated by any particular recent events. In other words, it was an exogenous shock to the rate-setting mechanism available to prospective Prosper borrowers. This allows us to measure the causal effect of auction availability by comparing the listings directly before and after the date of the change.

The identifying assumption required for this causal analysis is that in the days before and after December 19, 2010 there were no changes in the pool of people visiting the Prosper website. Then all changes in the pool of prospective borrowers listing on the site are due to borrowers' decisions. In other words, the same types of people are visiting the website but, due to the elimination of the auction, different types of people are deciding to actually post listings. Given the unanticipated nature of the change, this is a reasonable assumption. We further verify that the elimination of the auction was not highly publicized, as we could only find a few blog posts and articles noting the change in mechanism around the effective date.

The immediate effects of the termination of the auction process can be most clearly seen in Figure 3. Here the starting rates for loan listings by new borrowers are plotted around the time of the change.<sup>19</sup> Within each credit grade there is a clear and dramatic standardization at the time the auction system ends. The standardization actually occurs a few days earlier, because Prosper eliminated the ability of borrowers to pick their own starting rate a few days prior to the elimination of auction pricing. In addition to illustrating the uniformity of rates in the posted price setting, Figure 3 depicts a number of subsequent rate changes as Prosper experimented with their rate assignment algorithm. The timing of these subsequent rate changes and the introduction of additional maturity options are depicted in Figure 1.

The frequency of experimentation on the platform makes it clear that we need to focus on a narrow window around auction elimination in order to establish a causal estimate of

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<sup>19</sup>The x-axis of each figure denotes the filing date of the listing relative to December 19, 2010.



its effect. Wider ranges run the risk of including the effects of other platform changes. These risks are reinforced by Figure 4, which shows the daily number of listings within each credit grade. The graphs reveal significant and varied time trends. Most notable, there is an increase in the use of Prosper beginning roughly 40 business dates following auction elimination. In our analysis we are careful to avoid inference using these time periods. To this end, we limit our analysis to sixteen business days on either side of the date of auction retirement. We choose this particular number because it is the largest sample that excludes Prosper’s next experiment, a large unilateral rate decrease.

We estimate the causal effect of switching from the auction mechanism to centralized rate-setting using the following preferred specification:

$$y_{it} = \alpha + \beta Post_t + \gamma x_{it} + \varepsilon_{it}$$

where  $y_{it}$  is our outcome of interest for listing  $i$  on day  $t$ . Our outcomes of interest include various borrower characteristics, most notably a borrower’s credit experience.  $Post_t$  is an indicator for days after the auction was retired, and  $x_{it}$  is a vector of controls for borrower  $i$  at time  $t$ . The borrower controls include all other risk characteristics observable by the lender, including credit grade fixed effects. Our coefficient of interest is  $\beta$  which captures the effect of the elimination of the auction on the types of borrowers choosing to participate in Prosper’s credit market. This approach allow us to identify any changes in borrowers’ characteristics that are driven precisely by the loss of access to the auction setting. Although this is our preferred specification, we often supplement this with a specification that does not include  $\gamma x_{it}$ . This validates the robustness of our results and is necessary when we study outcomes that are not at the individual borrower level, such as the number of listings per day.

## 4 Results

In this section we study the causal effect of the elimination of the auction setting on households' selection into credit markets. First, we formalize the effects evident in Figures 3 and 4. Table 3 examines the effect of the auction change on interest rates and listings. All coefficients shown are estimates of  $\beta$ , the coefficient on the indicator for observations after the auction elimination. Columns 1-3 and 4-6 report the coefficient estimates for listings and loans, respectively. For both listings and funded loans we find that  $\beta$  is positive and significant, reflecting the interest rate increase depicted in Figure 3. Namely, we find that the starting rate for listings increased by approximately 3 percentage point whereas it only increased by 30 basis points for funded loans. We further show a significant decrease in the number of listings in Column 3. There are approximately 3 fewer listings per day once households are no longer able to obtain tailored interest rates. At the same time, there is no significant change in the number of funded loans. Thus some households choose to stop listing on the platform but this is not due to a change in the supply of funding.

Taken together, these results suggest that households derived some benefit from the auction setting above and beyond the ability to obtain a loan. A unique aspect of the auction process is that borrowers are able to receive feedback from a large number of lenders about the interest rate at which they are valued. These values are highly individualized and convey information about the rates more broadly available to these borrowers in credit markets. We posit that if households do use the platform to learn, this behavior would be more pronounced for less experienced households. Those with less experience in credit markets have likely accumulated less financial knowledge about the rates available to them. To test this hypothesis we estimate our specification with credit experience as our dependent variable and report the results in Table 4. We find that, on average, the borrowers listing on the website after the auction elimination have an additional year of credit experience, or 12.5% of a standard deviation. This is true even after controlling for all other observable borrower characteristics. These results support our hypothesis that feedback is an important

aspect of households' decisions to participate in the market.

To further test this interpretation we exploit heterogeneity in the pool of platform participants. A borrower's credit risk is an important determinant of their access to credit markets and the distributions of interest rates they face. As discussed in Section 2.2, higher risk borrowers have more upside to learning about their personal interest rate. Therefore we expect that for a given level of financial experience, higher risk households would benefit more from tailored feedback. Accordingly, we split our sample into higher and lower risk grades and repeat our estimation in Columns 3 and 4 of Table 4.

As hypothesized, we find that the increase in experience is driven by higher risk borrowers. Within higher credit grades, average credit experience increases by two years, 25% of a standard deviation. At the same time, there is no such change in experience for lower risk borrowers. These patterns are apparent in Figure 5, which plots average credit experience around the date of auction elimination. While credit length is continuous around the date for lower risk borrowers, it shifts up immediately for higher risk borrowers. Although our focus is on short term effects, we show in Table 5 that the observed changes in experience are persistent in the longer term as well. Credit history length significantly increases for higher risk borrowers for 40, 80, and 120 days following auction elimination whereas there are no changes over these time periods for lower risk borrowers.

A possible explanation for our results is that less experienced households were able to obtain more favorable rates than other households under the individualized rate regime. This would cause them to prefer the auction and disproportionately leave the platform once it is eliminated. To address these concerns, in Table 6 we study borrowers' listings from the beginning of June 2010 up until the auction is eliminated. We study the correlations between experience and listing attributes by regressing the attributes on all observable borrower characteristics, as well as listing month fixed effects. In Column 1 we can see that households with longer credit histories choose significantly higher starting rates for their loan listings. However, as shown in Column 2, there are no significant differences in the rate at which

they are actually funded. In addition, these households do not exhibit different propensities to default or charge-off loans. Our results suggest that less experienced households did not benefit from better credit terms under the auction regime. Instead, their actions are consistent with limited knowledge of their own riskiness. More so than other borrowers, they post listings at lower rates, at which they are unable to obtain a loan.

To better understand these patterns, in Table 7 we study how different borrowers react to failure to get funded. The sample in the table consists of potential borrowers who posted a listing but were not funded. It then studies the sequences of listings following this failure to fund. Listings are considered to be part of the sequence if the borrower submits a new listing within 30 days of the previous one. The coefficient on Credit Experience in Column 1 documents the same phenomenon as Table 6: more experienced borrowers use higher starting rates. The variable Repeat Listing is an indicator for all those after the first listing and the coefficient shows that borrowers' starting rates increase after their loan is not funded. However, the coefficient on the interaction term documents that this increase is smaller for more experienced borrowers. So less experienced borrowers react more aggressively to a failure to fund, suggesting they may learn more from lender feedback. This result holds when borrower characteristics are replaced by borrower fixed effects in Column 2. Overall these patterns support our hypothesis that auctions appeal to less experienced borrowers by helping them learn about their individual funding costs.

The analysis so far has focused on households that are new to the platform, as we conjecture that they benefit the most from receiving personalized feedback. At the same time, the length of credit experience is highly correlated with age. So it may be that the observed increase in credit history reflects the preference of a younger cohort for the auction setting, regardless of financial experience. To test for this possibility, we repeat the estimation of our baseline specification but restrict our sample to seasoned households, those who previously obtained a loan through Prosper. If the increase in credit experience is driven by an age or cohort effect we would expect the effects to be similar for seasoned and first-time borrowers.

We report the results in Table 8 and show that there is no significant change in credit experience for seasoned borrowers after the auction was retired. This lack of response suggests that the effects we measure are driven by experience length rather than age. It is further consistent with our hypothesis that borrowers value the learning possibilities through the auction. Seasoned borrowers have already successfully learned about their rates through the auction process, so for them additional feedback is less important.

We showed above that the documented change in average credit experience is not driven by changes in any other observable borrower characteristics, as we control for them. However, we want to determine whether any other borrower attributes respond to the change in mechanism. In Table 9 we estimate our baseline specification using various observable borrower characteristics as our dependent variables. In each regression we control for all other observable borrower characteristics, including length of credit experience. We find that there are no significant changes in any other attributes. Having ruled out changes in other observable characteristics, we investigate whether there are any concurrent changes in unobservable risk characteristics. We test whether there are any changes in loan performance that accompany the increase in borrowers' credit experience. In Table 10 we study default rates for loans around the elimination of the auction. We do not control for credit experience in these specifications, so any changes in default driven by changes in experience will be reflected in these results. We find that neither charge-off rates nor default rates change significantly.<sup>20</sup> In fact, the point estimates for these two delinquency outcomes have opposite signs, suggesting no consistent directional shift in delinquency. We conclude that the elimination of the auction uniquely affects borrowers with fewer years of credit experience and that this is unrelated to their loan performance.

So far, we have established that less experienced borrowers prefer auction rate setting to centralized rate setting. Moreover, this response is driven by the households that would

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<sup>20</sup>A couple of papers have found that default rates increase on Prosper around the elimination of the auction. Our approach differs by focusing on a shorter time period, to avoid conflating the effects of different experiments. We also differ in studying charged-off outcomes, which are much more common than default. In Appendix Table A2 we ensure that widening our window does not change our results.

benefit the most from tailored feedback on interest rates. However, there is an important alternative explanation that we now proceed to examine and rule out. As documented earlier in Table 3, the elimination of individualized pricing through auctions was accompanied by an increase in both listed and funded interest rates. If less experienced borrowers are more sensitive to interest rates, perhaps due to different outside options, this would differentially affect their participation in the credit market. In order to disentangle the effect of this rate hike from the effect of removing tailored feedback, we use another natural experiment. Almost a month after the auction change, on January 13, 2011, Prosper instituted a unilateral rate decrease. The resulting sharp drop in rates can be easily seen in Figure 3.

We use the same empirical approach as we did for auction to study the effect of this rate drop. Table 11 reports the results of estimating our baseline specification around the rate drop. Columns 1 and 2 show a significant rate decrease of 1.4 percentage points. This drop is approximately half as large as the rate increase coupled with the auction elimination. These lower rates attracted more borrowers to the platform, as documented in Column 3. The number of listings per day increased by 1.7, an increase roughly half the size of the participation decrease prompted by the auction experiment. However, there is no accompanying change in credit experience.<sup>21</sup> Therefore, it is not the level of the interest rate that induced less experienced households to leave the platform but rather the change in the interest rate assignment mechanism.

In a final set of robustness checks we ensure that our results are not driven by industry or seasonal effects. First we consider that there may be industry-wide changes affecting online peer-to-peer lending at the end of December 2010. We collect data on Prosper’s main competitor, Lending Club. Since inception, Lending Club used centralized rate assignment, so it offers a natural placebo test. The results of running our empirical analysis on Lending Club’s data are in Panel A of Table 12. They demonstrate that there were no changes in

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<sup>21</sup>We are assuming in this analysis that less experienced households respond to both rate increases and decreases. One may worry that they are less aware of rate declines and therefore do not react to the rate drop. We contend that this is unlikely because younger, less experienced, households are actually more likely to engage in rate shopping. We use data from the SCF to show this in Appendix Table A1.

interest rates, volume, or credit experience at the time of Prosper’s change. Next we test whether our results could be driven by seasonal patterns for the end of December. We reproduce our analysis using data on Prosper exactly one year prior. In Panel B of Table 12 we test for changes around December 19, 2009. We find that there is a significant decrease in starting rates, but that this disappears after controlling for borrower characteristics. More importantly, there are no changes in borrower participation or in the average credit experience of the borrower pool. We conclude that the effects we measure are driven solely by the elimination of the auction.

## 5 Conclusion

In this paper we document that households with less credit experience place more value on the ability to receive feedback about interest rates. To show this, we exploit a quasi-natural experiment in an online consumer credit market. Prosper, a large peer-to-peer lending platform unexpectedly switched from auction pricing of loans to centralized pricing of broadly similar borrowers. In an immediate response, less experienced households disproportionately exit this market. We show that these results are consistent with demand from less experienced households for learning from the interactive auction process. We further rule out alternative explanations such as changes in interest rate levels, borrower risk profiles, or favorable treatment under auction.

Our findings highlight an important intersection between household finance and financial innovation that has not yet been studied. They suggest that financial and technological innovation can enable less experienced households to obtain important financial knowledge at a low cost. While our results rely on data from a specific online platform, we believe that the implications are not restricted to this sample and are highly relevant for near-prime households with high outstanding revolving debt. As discussed in 2.2 the higher risk households in our sample, for which our results are most striking, are near-prime borrowers

who have access to credit card markets. Many of these households have accumulated a large amount of outstanding debt at high interest rates. As US household debt levels continue to rise, these households are increasingly drawing the focus of policymakers. Our paper promotes the understanding of the behavior of these households, in particular how financial innovation could be used to improve their overall financial health.

The implications of our findings for policymakers are twofold. First, we document that less experienced households search for feedback and value learning about their credit market options. Anecdotal evidence suggests borrowers, especially less experienced ones, do not shop for interest rates. Yet prior research suggests that shopping for interest rates could have a significant effect on credit market outcomes (Stango and Zinman, 2016). One possible explanation for limited shopping is borrowers' lack of understanding of these markets, and not realizing a better interest rate may be available to them. While we do not rule out this line of reasoning in this paper, we do show that there is demand for credible information about tailored interest rates from near-prime households. Accordingly, our findings suggest that cost and the mechanism by which tailored rates are conveyed to households are important. Further, they have an important role to play in inducing households to acquire financial knowledge.

The second implication of our results is that financial innovation has the potential to meet households' desire to learn about their interest rates. Advances in financial technology and the booming FinTech industry have raised key questions about how households will be impacted. While innovation has made it easier for households to access credit markets, it has also made it possible to develop more complex financial products (Campbell, 2016). These increases in complexity combined with increased access could be problematic, specifically for households with less financial experience. However, in this paper, we show that financial innovation may also play a role in allowing households to more easily acquire financial knowledge. By making individualized interest rates more accessible and easier to find, financial innovation can help less experienced borrowers better understand their funding costs. In



addition to documenting this overlooked role of financial innovation, our results may help regulators identify a mechanism that facilitates such learning. Thus our findings may be valuable for designing future regulations.

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Figure 1: Changes in Interest Rates and Maturity After Auction Elimination

**Notes:** Event dates and description taken from Prosper's SEC filings prospectuses.

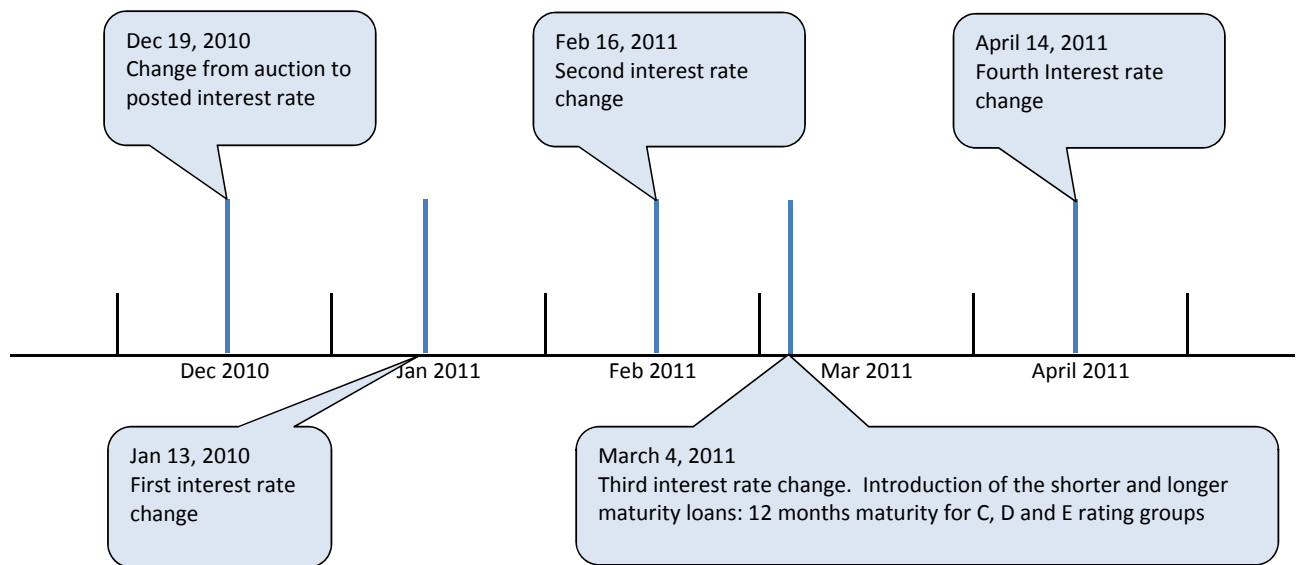
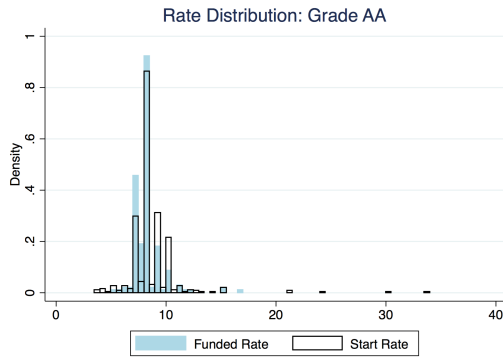
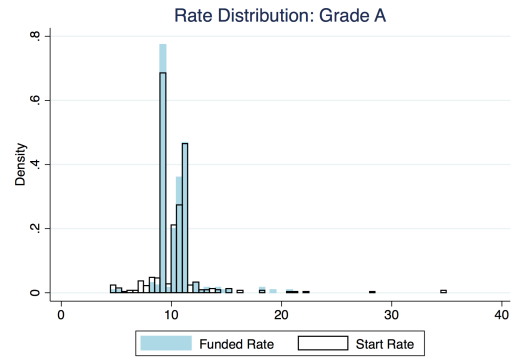


Figure 2: Interest Rate Dispersion in Auctions

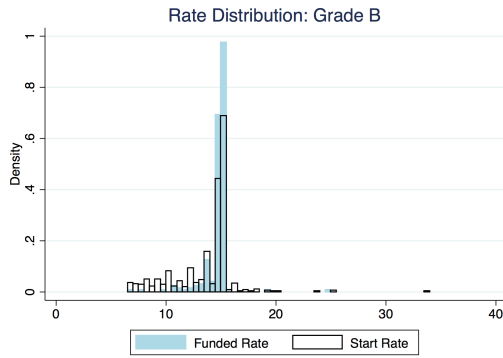
**Notes:** Each graph depicts the listed and funded interest rates faced by borrowers in a certain credit grade. The start rate is the reserve rate listed by the borrower and the funded rate is the rate at which the loan is actually issued. Credit grades are assigned by Prosper based on proprietary analysis. The period begins on June 1, 2010 and ends on the last day of auction pricing. Listings are restricted to 3-year loans for borrowers that do not have a prior loan with the platform.



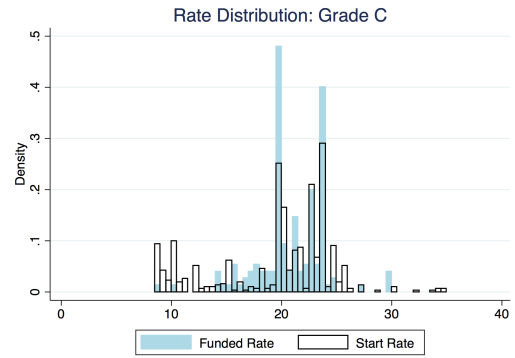
(a)



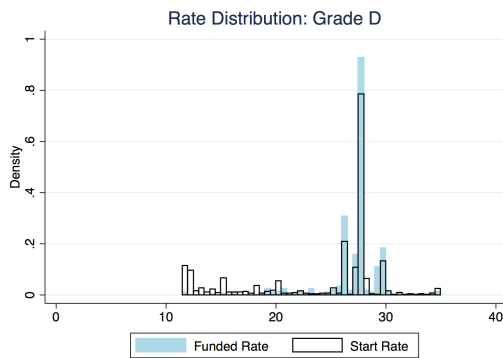
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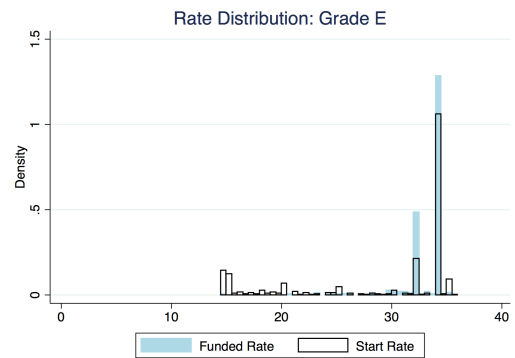
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Figure 3: Rates During and After Auction Pricing

**Notes:** Each graph depicts the average interest rate listed by borrowers in a single credit grade. Credit grades are assigned by Prosper based on proprietary analysis. The x-axis measures the number of filing dates relative to the date on which the auction was eliminated (December 19, 2010). Each dot represents a 2-day average. During the auction period, the rates shown are the starting rate for the auction. Listings are restricted to 3-year loans for borrowers that do not have a prior loan with the platform.

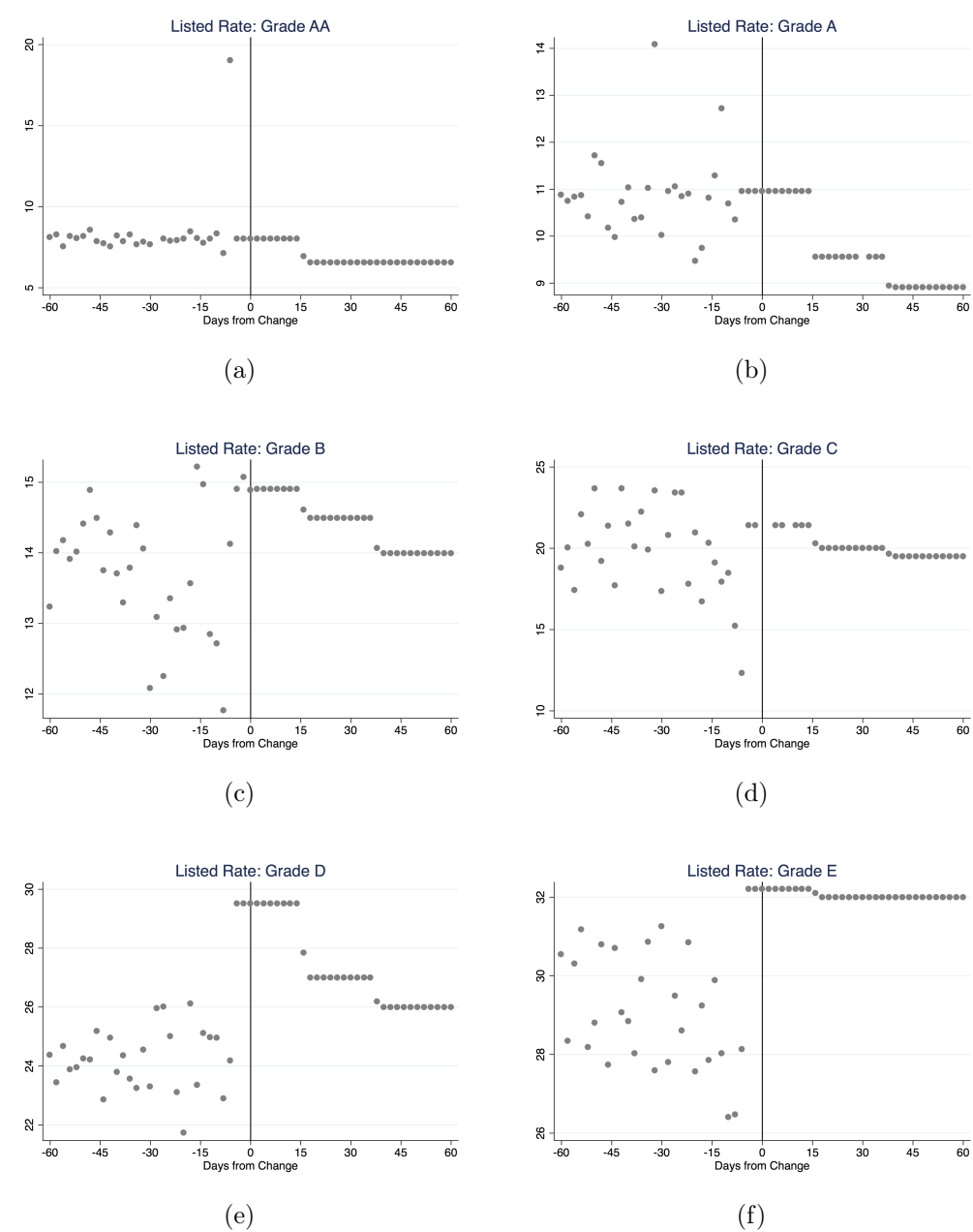


Figure 4: Number of Listings During and After Auction Pricing

**Notes:** Each graph depicts the number of listings by borrowers in a single credit grade. Credit grades are assigned by Prosper based on proprietary analysis. The x-axis measures the number of filing dates relative to the date on which the auction was eliminated (December 19, 2010). Each dot represents the average daily number of listings for a 2-day period. Listings are restricted to 3-year loans for borrowers that do not have a prior loan with the platform.



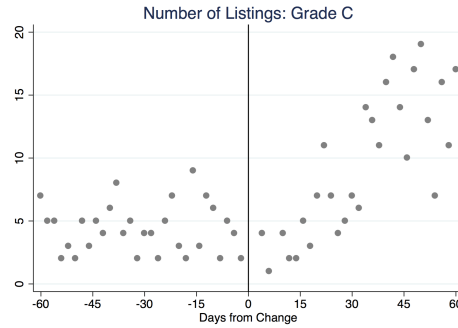
(a)



(b)



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(e)



(f)



Figure 5: Length of Credit Experience During and After Auction Pricing

**Notes:** Each graph depicts the average credit experience of borrowers listing in a single credit grade. Credit experience is defined as the number of years since the first credit line. Credit grades are assigned by Prosper based on proprietary analysis. The x-axis measures the number of filing dates relative to the date on which the auction was eliminated (December 19, 2010). Each dot represents a 2-day average. Listings are restricted to 3-year loans for borrowers that do not have a prior loan with the platform.



(a)



(b)



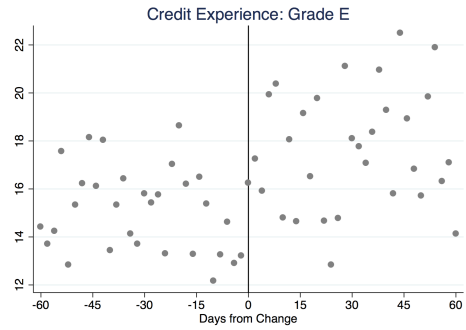
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(f)

Table 1: Summary Statistics for Listings

**Notes:** This table shows summary statistics for all listings, and separately for lower risk (AA-C) and higher risk (D-E) listings, as categorized by Prosper. All listings were created from June 2010 through June 2011. The Start Rate is the rate posted by the borrower. The amount of the loan request is in dollars. Days Listed is the number of days between the start and end of the listing. Funded is an indicator for whether a listing is successfully funded. FICO is approximated as the mean of the borrower’s 20-point range. Credit experience is measured as the number of years since the borrower’s first credit line was opened. Revolving balance refers to the total outstanding balance that the borrower owes on open revolving credit accounts (in thousands of dollars). DTI is the sum of the borrower’s monthly debt payments divided by their monthly income, capped at 10. Utilization is the sum of balances owed on open bankcards divided by the sum of their credit limits. Current lines is the number of credit lines that the borrower is paying on time. Open lines is the number of credit lines open. Has Inquiry denotes the existence of a credit inquiry within the last 6 months. Has Public Record indicates the presence of bankruptcies, liens, and judgements within the past 10 years. Has Delinquencies indicates the presence of any delinquencies within the last 7 years. Income refers to reported labor income and is measured in thousands of dollars. Months employed refers to the number of months that the borrower has held their current job. The final four lines describe the stated reason for requesting the loan. Listings are restricted to 3-year loans for borrowers that do not have a prior loan with the platform.

	All Listings		Lower Risk		Higher Risk	
	Mean	StDev	Mean	StDev	Mean	StDev
Start Rate	21.5	8.74	13.2	4.92	27.1	5.79
Amount	7,262	4,831	8,981	5,808	6,091	3,587
Days Listed	6.08	3.91	6.34	3.94	5.91	3.88
Funded	.387	.487	.418	.493	.367	.482
~ FICO	725	52.1	762	47.9	700	38.2
Credit Experience	16.4	8.16	17.4	8.32	15.7	7.98
Revolv. Balance	21.7	39.7	23.3	43.2	20.5	37.2
DTI	.233	.357	.192	.168	.264	.445
Utilization	.477	.32	.365	.281	.554	.322
Current Lines	9.09	5.2	9.56	5.08	8.77	5.26
Open Lines	8.07	4.72	8.55	4.63	7.74	4.76
Has Inquiry	.52	.5	.436	.496	.578	.494
Has Public Record	.168	.374	.11	.313	.207	.405
Has Delinquencies	.24	.427	.148	.355	.303	.459
Income	70.4	141	80.1	129	63.8	149
Months Employed	83	87.7	84.4	88.7	82	87
Homeowner	.486	.5	.591	.492	.415	.493
For Debt Consol.	.446	.497	.45	.498	.443	.497
For Home	.0927	.29	.117	.322	.0759	.265
For Business	.132	.338	.131	.337	.133	.339
For Auto	.0577	.233	.0521	.222	.0615	.24
Observations	10365		4202		6163	

Table 2: Summary Statistics for Funded Loans

**Notes:** This table shows summary statistics for all listings, and separately for lower risk (AA-C) and higher risk (D-E) listings, as categorized by Prosper. All listings were created from June 2010 through June 2011. Borrower characteristics are defined as in Table 1. The End Rate is the rate at which the loan is successfully funded. Bids Filled is the number of lenders that successfully funded the loan. Charged Off indicates whether a loan is more than 120 days past due. Defaulted indicates whether a loan has defaulted by the end of December 2014. Listings are restricted to 3-year loans for borrowers that do not have a prior loan with the platform.

	All Loans		Lower Risk		Higher Risk	
	Mean	StDev	Mean	StDev	Mean	StDev
End Rate	22.1	8.79	13.1	4.54	29	3.22
Amount	5,994	4,046	7,715	4,965	4,658	2,421
Days Listed	6.04	4.1	6.58	4.06	5.62	4.08
Bids Filled	112	86.2	155	103	77.5	46.3
~ FICO	722	51.6	756	47.9	695	35.7
Credit Experience	16.3	7.7	16.8	7.71	15.9	7.68
Revolv. Balance	19.8	36.6	21	40	18.8	33.7
DTI	.217	.354	.174	.121	.253	.465
Utilization	.496	.32	.385	.277	.583	.324
Current Lines	8.91	5.08	9.4	4.86	8.53	5.21
Open Lines	7.88	4.58	8.39	4.39	7.48	4.68
Has Inquiry	.485	.5	.381	.486	.565	.496
Has Public Record	.199	.4	.133	.339	.251	.434
Has Delinquencies	.271	.445	.18	.384	.342	.475
Income	68.5	138	75.5	61.9	63	175
Months Employed	80.9	85.2	79.6	82.5	81.9	87.3
Homeowner	.504	.5	.595	.491	.432	.496
For Debt Consol.	.459	.498	.477	.5	.445	.497
For Home	.0979	.297	.119	.323	.0819	.274
For Business	.103	.305	.103	.304	.104	.305
For Auto	.0571	.232	.0473	.212	.0646	.246
Charged Off	.141	.348	.0689	.253	.197	.397
Defaulted	.068	.252	.0393	.194	.0903	.287
Observations	4014		1755		2259	

Table 3: Overall Changes Around Auction Elimination

**Notes:** This table shows how rates and the number of listings change around the elimination of the auction. Columns (1)-(3) focus on listings and their start rates. Columns (4)-(6) focus on loans and their end rates. Rates are measured at the listing level and the number of listings or loans are at the day-risk-grade level. The sample includes listings from 16 filing dates before and after the change. The independent variable Post is an indicator for days on or after December 19, 2010. All regressions include credit grade fixed effects. Borrower characteristics include all borrower credit variables available, stated income, months employed, homeownership, and stated loan reason. Listings are restricted to 3-year loans for borrowers that do not have a prior loan with the platform. Robust standard errors are in parentheses.

\* p<.05 \*\* p<.01 \*\*\*p<.001

	(1) Start Rate	(2) Start Rate	(3) # Listings	(4) End Rate	(5) End Rate	(6) # Listings
Post	2.84*** (.241)	2.94*** (.269)	-3.15*** (.672)	.422*** (.123)	.304** (.0968)	-.731 (.389)
Borrower Xs	No	Yes	No	No	Yes	No
$R^2$	0.724	0.761	0.466	0.975	0.984	0.397
Sample	All	All	All	Funded	Funded	Funded
Observations	942	797	168	464	405	143

Table 4: Credit Experience Around Auction Elimination

**Notes:** This table estimates changes in credit experience around the elimination of the auction. Experience is measured as the number of years since the borrower's first credit line. The sample includes listings from 16 filing dates before and after the change. The independent variable Post is an indicator for days on or after December 19, 2010. All regressions include credit grade fixed effects. Borrower characteristics include all borrower credit variables available, stated income, months employed, homeownership, and stated loan reason. Listings are restricted to 3-year loans for borrowers that do not have a prior loan with the platform. Funded listings include only those that are fully funded. The high risk sample refers to grades D-E and the low risk sample refers to grades AA-C. Listings are restricted to 3-year loans for borrowers that do not have a prior loan with the platform. Robust standard errors are in parentheses.

\* p<.05 \*\* p<.01 \*\*\*p<.001

	(1) Credit Experience	(2) Credit Experience	(3) Credit Experience	(4) Credit Experience
Post	1.6** (.564)	1.07* (.522)	2** (.668)	-.0228 (.811)
Borrower Xs	No	Yes	Yes	Yes
$R^2$	0.045	0.334	0.326	0.411
Sample	All	All	Higher Risk	Lower Risk
Observations	942	797	491	306

Table 5: Longer Term Effects on Credit Experience

**Notes:** This table estimates changes in credit experience around the elimination of the auction. Experience is measured as the number of years since the borrower's first credit line. The independent variable Post is an indicator for days on or after December 19, 2010. All regressions include credit grade fixed effects. Borrower characteristics include all borrower credit variables other than the dependent variable, including credit experience. The high risk sample refers to grades D-E and the low risk sample refers to grades AA-C. Listings are restricted to 3-year loans for borrowers that do not have a prior loan with the platform. Robust standard errors are in parentheses.

\* p<.05 \*\* p<.01 \*\*\*p<.001

	(1)	(2)	(3)	(4)	(5)	(6)
Post	1.87*** (.381)	1.47*** (.23)	1.08*** (.185)	-.161 (.467)	.0556 (.307)	-.0503 (.244)
Borrower Xs	Yes	Yes	Yes	Yes	Yes	Yes
$R^2$	0.287	0.261	0.266	0.297	0.252	0.238
Sample	Higher Risk	Higher Risk	Higher Risk	Lower Risk	Lower Risk	Lower Risk
Window	40	80	120	40	80	120
Observations	1580	3780	5367	998	2459	4024

Table 6: Listing Behavior in Auction, By Experience

**Notes:** This table studies the listings submitted by potential borrowers under the auction system. Column (1) studies all listings whereas columns (2)-(4) focus on fully funded loans. The period begins on June 1, 2010 and ends on the last day of auction pricing. All regressions include controls for all observable borrower characteristics, credit grade fixed effects, and listing month fixed effects. Listings are restricted to 3-year loans for borrowers that do not have a prior loan with the platform. Robust standard errors are in parentheses.

\*  $p < .05$  \*\*  $p < .01$  \*\*\* $p < .001$

	(1) Start Rate	(2) End Rate	(3) Charged Off	(4) Defaulted
Credit Experience	0.0538*** (0.0110)	0.0081 (0.0078)	0.0007 (0.0012)	0.0012 (0.0010)
Borrower Xs	Yes	Yes	Yes	Yes
$R^2$	0.657	0.955	0.051	0.035
Sample	All	Funded	Funded	Funded
Observations	5108	1560	1560	1560

Table 7: Repeat Listings in Auction, By Experience

**Notes:** This table studies the repeat listings of borrowers under the auction system. The sample studied consists of sequences of listings submitted by potential borrowers. Listings are considered a repeat listing if the same borrower submits a new listing within 30 days of a previous one. The sample includes only those borrowers who do not get funded on their first listing. The period begins on June 1, 2010 and ends on the last day of auction pricing. Listings are restricted to 3-year loans for borrowers that do not have a prior loan with the platform. Robust standard errors are in parentheses.

\*  $p < .05$  \*\*  $p < .01$  \*\*\* $p < .001$

	(1) Start Rate	(2) Start Rate
Credit Experience	0.0747*** (0.0150)	
Repeat Listing	3.2355*** (0.4309)	2.8492*** (0.3522)
Credit Experience x Repeat Listing	-0.0538* (0.0223)	-0.0510** (0.0195)
Borrower Xs	Yes	No
Borrower FE	No	Yes
$R^2$	0.624	0.881
Sample	All	All
Observations	4117	2895



Table 8: Credit Experience of Previous Borrowers Around Auction Elimination

**Notes:** This table estimates changes in credit experience around the elimination of the auction. Only borrowers that have previously taken out a loan from the platform are included. Experience is measured as the number of years since the borrower's first credit line. The sample includes listings from 16 filing dates before and after the change. The independent variable Post is an indicator for days on or after December 19, 2010. All regressions include credit grade fixed effects. Borrower characteristics include all borrower credit variables available, stated income, months employed, homeownership, and stated loan reason. Listings are restricted to 3-year loans for borrowers that do not have a prior loan with the platform. Funded listings include only those that are fully funded. The high risk sample refers to grades D-E and the low risk sample refers to grades AA-C. Listings are restricted to 3-year loans for borrowers that do not have a prior loan with the platform. Robust standard errors are in parentheses.

\* p<.05 \*\* p<.01 \*\*\*p<.001

	(1) Credit Experience	(2) Credit Experience	(3) Credit Experience	(4) Credit Experience
Post	.748 (1.08)	-.325 (.922)	.654 (1.5)	-.913 (.987)
Borrower Xs	No	Yes	Yes	Yes
$R^2$	0.017	0.417	0.487	0.491
Sample	All	All	Higher Risk	Lower Risk
Observations	266	245	142	103

Table 9: Borrower Characteristics Around Auction Elimination

**Notes:** This panel studies how borrower characteristics change around the elimination of the auction. Credit variables are as defined in Table 1. The sample includes loans from 16 filing dates before and after the change. The independent variable Post is an indicator for days on or after December 19, 2010. All regressions include credit grade fixed effects. Borrower characteristics include all borrower credit variables other than the dependent variable, including credit experience. Listings are restricted to 3-year loans for borrowers that do not have a prior loan with the platform. Robust standard errors are in parentheses.

\* p<.05 \*\* p<.01 \*\*\*p<.001

	Ln(Revolv)	DTI	Utilization	Current Lines	Open Lines	Has Inquiry	Has Public Record	Has Delinq.
Post	.11 (.0606)	.00484 (.0325)	-.0143 (.0164)	-.204 (.112)	.128 (.0956)	-.0236 (.0323)	.0165 (.0257)	-.00888 (.0282)
Borrower Xs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$R^2$	0.617	0.490	0.562	0.897	0.893	0.288	0.292	0.297
Observations	797	797	797	797	797	797	797	797

	Ln(Income)	Ln(Months Empl.)	Homeowner	For Debt Consol.	For Home	For Business	For Auto
Post	.0157 (.034)	-.148 (.104)	-.0462 (.0315)	.00207 (.0356)	.0226 (.0206)	.0233 (.025)	.0217 (.0171)
Borrower Xs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$R^2$	0.603	0.110	0.323	0.101	0.081	0.040	0.070
Observations	797	797	797	797	797	797	797

Table 10: Loan Performance Around Auction Elimination

**Notes:** This table estimates changes in loan outcomes around the elimination of the auction. Panel A measures whether the loan was charged off and Panel B measures if it defaulted. The sample includes listings from 16 filing dates before and after the change. The independent variable Post is an indicator for days on or after December 19, 2010. All regressions include credit grade fixed effects. Borrower characteristics include all borrower credit variables available, stated income, months employed, homeownership, and stated loan reason. Listings are restricted to 3-year loans for borrowers that do not have a prior loan with the platform. The high risk sample refers to grades D-E and the low risk sample refers to grades AA-C. Loans are restricted to fully-funded 3-year loans for borrowers that do not have a prior loan with the platform. Robust standard errors are in parentheses.

\* p<.05 \*\* p<.01 \*\*\*p<.001

Panel A: Charged Off

	(1)	(2)	(3)	(4)
Post	-.0311 (.0318)	-.0218 (.0332)	-.0321 (.0506)	-.0241 (.0389)
Borrower Xs	No	Yes	Yes	Yes
$R^2$	0.033	0.117	0.109	0.211
Sample	All	All	Higher Risk	Lower Risk
Observations	464	405	244	161

Panel B: Defaulted

	(1)	(2)	(3)	(4)
Post	.0157 (.024)	.0166 (.0259)	.0512 (.0367)	-.0229 (.0367)
Borrower Xs	No	Yes	Yes	Yes
$R^2$	0.034	0.086	0.067	0.256
Sample	All	All	Higher Risk	Lower Risk
Observations	464	405	244	161

Table 11: Placebo Test: Changes Around Rate Decrease

**Notes:** This table studies changes in listings around the unilateral rate decrease on January 13, 2011. Rates and credit experience are measured at the listing level and the number of listings are at the day-risk-grade level. The sample includes listings from 16 filing dates before and after the change. The independent variable Post is an indicator for days on or after January 13, 2011. All regressions include credit grade fixed effects. Borrower characteristics include all borrower credit variables available, stated income, months employed, homeownership, and stated loan reason. The high risk sample refers to grades D-E and the low risk sample refers to grades AA-C. Listings are restricted to 3-year loans for borrowers that do not have a prior loan with the platform. Robust standard errors are in parentheses.

\* p<.05 \*\* p<.01 \*\*\*p<.001

	(1) Start Rate	(2) Start Rate	(3) # Listings	(4) Credit Experience	(5) Credit Experience	(6) Credit Experience	(7) Credit Experience
Post Drop	-1.42*** (.0388)	-1.41*** (.0424)	1.7*** (.453)	-.612 (.595)	-.379 (.552)	.183 (.734)	-1.16 (.802)
Borrower Xs	No	Yes	No	No	Yes	Yes	Yes
$R^2$	0.997	0.997	0.472	0.003	0.281	0.280	0.364
Sample	All	All	All	All	All	Higher Risk	Lower Risk
Observations	823	714	176	823	714	405	309

Table 12: Placebo Tests: Industry and Calendar Effects

**Notes:** Panel A studies changes in listings on Lending Club around the date of auction elimination. Panel B studies changes in listings on Prosper exactly one year prior to the date of auction elimination. Rates and credit experience are measured at the listing level and the number of listings are at the day-risk-grade level. Post is an indicator for days on or after December 19, 2010. Post - 1 Year is an indicator for days on or after December 19, 2009. All regressions include credit grade fixed effects. Borrower characteristics include all borrower credit variables available. They also include stated income, months employed, homeownership, and stated loan reason, when available. The high risk sample refers to grades D-E and the low risk sample refers to grades AA-C. Listings are restricted to 3-year loans for borrowers that do not have a prior loan with the platform.

\* p<.05 \*\* p<.01 \*\*\*p<.001

## Panel A: Lending Club

	(1) Rate	(2) Rate	(3) # Listings	(4) Credit Experience	(5) Credit Experience	(6) Credit Experience	(7) Credit Experience
Post	.113 (.0666)	.106 (.06)	16.2 (8.98)	.307 (.248)	.242 (.215)	.0558 (.302)	.418 (.305)
Borrower Xs	No	Yes	No	No	Yes	Yes	Yes
$R^2$	0.751	0.797	0.059	0.011	0.262	0.296	0.227
Sample	All	All	All	All	All	Higher Risk	Lower Risk
Observations	3577	3566	54	3577	3566	1745	1821

## Panel B: One Year Prior

	(1) Start Rate	(2) Start Rate	(3) # Listings	(4) Credit Experience	(5) Credit Experience	(6) Credit Experience	(7) Credit Experience
Post - 1 Year	-.637* (.304)	-.329 (.33)	-.885 (1.28)	-.734 (.444)	-.595 (.402)	-.296 (.588)	-.963 (.542)
Borrower Xs	No	Yes	No	No	Yes	Yes	Yes
$R^2$	0.668	0.709	0.246	0.033	0.288	0.326	0.318
Sample	All	All	All	All	All	Higher Risk	Lower Risk
Observations	1208	963	137	1208	963	428	535

# A Appendix

Table A1: Evidence on Propensity to Shop for Credit

**Notes:** The data below is taken from the Survey of Consumer Finance of 2010. Non-shopper is an indicator for those households that indicate they engage in “almost no shopping” when deciding about borrowing money or obtaining credit. The sample “Internet” is constructed by using only those households that indicated they use the internet to make decisions about borrowing or credit. Standard errors are in parentheses.

\*  $p < .05$  \*\*  $p < .01$  \*\*\* $p < .001$

	(1) Non-Shopper	(2) Non-Shopper
Age	.0126*** (.00213)	.0134*** (.0026)
Ln(Revolv)	-.016 (.021)	.0197 (.0205)
DTI	-.00755 (.0802)	-.269*** (.0729)
Open Lines	-.181* (.0737)	-.112 (.0739)
Ln(Income)	-.161** (.0552)	-.303*** (.0525)
Homeowner	-.183* (.0738)	-.0577 (.0797)
Sample	All	Internet

Table A2: Longer Term Effects on Loan Performance

**Notes:** This table estimates changes in loan outcomes around the elimination of the auction. Panel A measures whether the loan was charged off and Panel B measures if it defaulted. The independent variable Post is an indicator for days on or after December 19, 2010. All regressions include credit grade fixed effects. Borrower characteristics include all borrower credit variables other than the dependent variable, including credit experience. The high risk sample refers to grades D-E and the low risk sample refers to grades AA-C. Loans are restricted to 3-year loans for borrowers that do not have a prior loan with the platform. Robust standard errors are in parentheses.

\* p<.05 \*\* p<.01 \*\*\*p<.001

## Panel A: Charged Off

	(1)	(2)	(3)	(4)	(5)	(6)
Post	-.017 (.0318)	-.0251 (.0261)	.00988 (.0219)	-.0182 (.0301)	-.0169 (.0217)	.0121 (.0137)
Borrower Xs	Yes	Yes	Yes	Yes	Yes	Yes
$R^2$	0.197	0.088	0.081	0.126	0.069	0.050
Sample	Higher Risk	Higher Risk	Higher Risk	Lower Risk	Lower Risk	Lower Risk
Window	40	80	120	40	80	120
Observations	255	588	953	212	453	819

## Panel B: Defaulted

	(1)	(2)	(3)	(4)	(5)	(6)
Post	-.000839 (.031)	-.0102 (.0198)	.00192 (.0178)	.00933 (.0172)	.00464 (.00897)	.00237 (.00929)
Borrower Xs	Yes	Yes	Yes	Yes	Yes	Yes
$R^2$	0.088	0.063	0.047	0.117	0.050	0.040
Sample	Higher Risk	Higher Risk	Higher Risk	Lower Risk	Lower Risk	Lower Risk
Window	40	80	120	40	80	120
Observations	255	588	953	212	453	819