Allocation Incentives of Marketplace Lending Platforms during the IPO of Debt Securities

Abstract

Marketplace lending platforms create new (debt) securities similar to the underwriters of an IPO. For both, revenue (origination fees to marketplace lending platforms and underwriting spread to IPO underwriters) is proportional to the volume of securities created. Yet, when it comes to the allocation of these newly issued securities, marketplace lending platforms claim to randomly allocate securities among investors while IPO underwriters preferentially allocate. We provide evidence that the allocation behavior of marketplace lending platforms is not random and favors certain investors at the expense of others. Motivated by the underwriter literature and originate-to-distribute models of intermediation, we explore channels to explain why marketplace lending platforms might preferentially allocate securities to particular investors. Our results suggest a tension between adverse selection issues within the institutional market that force platforms to preferentially allocate and an opposing channel caused by heavy securitization activity of the marketplace lending notes which reduces the platforms' preferential allocation of loans to institutional investors.

JEL Classifications: G21, G23, L81, D53, G28

Keywords: IPO, Underwriter Allocation, Peer-to-peer lending, FinTech, Marketplace Lending, Crowdfunding, financial intermediation, securitization

Technology has substantially lowered the bar to create new securities. Financial technology firms such as marketplace lending platforms, crowdfunding platforms, and decentralized autonomous organizations (DAOs) have innovated new ways to match capital suppliers with capital demanders. Research on the incentives motivating these organizations is sparse because of their newness. In this paper, we delve into the incentives behind the most mature of these emerging organizations, marketplace lending platforms.

In one sense, marketplace lending platforms are agents with a similar objective to equity/bond underwriters. They intermediate the creation of a security (debt contract) for borrowers and the sale of these securities to capital providers (investors). The main source of marketplace lending platforms' revenue is the origination fee they charge to borrowers as a percentage of the borrower's loan amount. Thus, the key driver of the marketplace lending platform's revenue is the volume of loans originated. The IPO literature suggests a similar volume motive encourages underwriter behavior such as IPO underpricing (Loughran and Ritter, 2002) and preferentially allocation of securities to institutional investors (Goldstein et al., 2011). In contrast to the IPO underwriters, marketplace lending platforms claim to randomly allocate securities between retail and institutional investors. Our objective in this paper is twofold. First, we test if securities are truly randomly allocated among investors given the volume motive of marketplace lending platforms. Second, we explore incentive channels that may exist for these new security underwriters that may drive preferential allocation.

Developing an understanding of platform incentives is important for three reasons. First, the size and scope of these newly emerging organizations are economically significant. Marketplace lending platforms began around 2006 and initially originated only personal unsecured loans. By 2017, the major marketplace lending platforms originated nearly a third of the personal unsecured loans in the United States according to TransUnion and have expanded into automotive financing, residential mortgages, small business lending, and student loan financing.[1] These lending segments compose a substantial portion of the traditional commercial bank's loan portfolio and represent a significant threat to the

[1] https://www.transunion.com/blog/fact-or-fiction-are-fintechs-different-than-other-lenders

traditional model of depository lending. Furthermore, the Regulation Crowdfunding (CF) portion of the JOBS Act took effect in May of 2016 and 229 firms have successfully raised capital while 708 firms had filed with the SEC to begin a crowdfunding campaign through 2017. Additionally, DAO's raised $12 billion in startup capital through the initial coin offering (ICO) process (Kostovetsky and Benedetti, 2018) in 2017, outstripping the initial round capital raised by venture capital markets that year by an estimated $3.5 billion.[2] Taken together, these technological changes appear to represent a meaningful shift in the capital formation markets.[3]

Second, the equity IPO literature repeatedly demonstrates the incentives of underwriters matter (Lowry et al., 2017). However, as Vallee and Zeng (2018) show, the incentives of the platforms can lead to unique behavior relative to traditional intermediaries. They demonstrate that platforms optimize the amount of information published on borrowers to maximize their loan origination volume. In their model and empirical tests, they show that platforms may optimally *reduce* information on applicants available to investors. By doing so, the platform is able to minimize adverse selection issues between investors (retail and institutional) which results in maximum origination volume. Because technology is creating new ways to match capital providers with capital demanders, it is likely that the classic incentive issues may mold intermediary behavior in new ways.

Finally, because these organizations are in their infancy, further study is important so that a proper regulatory structure can be established. An overly burdensome regulatory approach can easily stifle the innovativeness of the platforms (Venkatesan et al., 2018), yet too light-handed an approach exposes retail investors to substantial risk (Jackson et al., 2016). Understanding the incentives behind different security creation platforms would seem to be a critical first step toward selecting optimal regulatory policies.

As mentioned above, our goal is to begin with a simple examination of allocation behavior. Marketplace lending platforms take borrower loan requests and allocate them to two funding markets

[2] https://news.crunchbase.com/news/q4-2017-global-report-vc-sets-annual-records-back-strong-late-stage-results/
[3] There have been 708 unique Form C filings and 229 Form C/U filings through 2017.

where investors compete to fund the loans. In our analysis, we study LendingClub and Prosper, yet this structure is also common to other lending platforms such as Funding Circle. The platforms must choose which market to initially assign a loan, either to a retail (fractional) funding market or an institutional (whole) funding market. We test the assertion that platforms randomly allocate loans to retail/institutional investors and find evidence that while both platforms under study claim to allocate loans randomly, both preferentially allocate loans to a particular group of investors. We estimate loan default dependency using a hazard model and find that on average, loans allocated to LendingClub's institutional investors have a 3.1% lower conditional default rate. In a similar test, we show that the allocation of loans to the institutional market on Prosper is substantially worse than the allocation to retail investors for the investment grade loan segment with a 7.1% higher hazard rate. Note in both cases, our test is absent the investor's funding decision but simply conditioned on the allocation decision of the platform. We also find evidence that loans allocated to LendingClub's institutional investors have a 1.3% lower conditional prepayment rate while the Prosper decision to allocate to the institutional market holds no association with conditional prepayment rate. We run a battery of robustness tests to account for time series changes on the platforms, potential selection issues, and even simultaneous hazards (prepayment and default) yet these baseline results appear to hold.

In a sense, the base results are simultaneously surprising and expected. While the preferential allocation behavior of LendingClub conflicts with the company's assertion that the loans are randomly allocated, it is not surprising to find preferential allocation behavior among IPO underwriters with similar objective functions. In the same sense, Prosper's preferential allocation is surprising because institutional investors provide the majority of capital that drives the platforms' origination activity. These results drive us to the second portion of the paper where we consider incentives behind allocation behavior in marketplace lending.

We examine three potential channels that could drive allocation behavior. Initially, we examine if adverse selection within the institutional market may drive platforms to preferentially allocate. Similar to the adverse selection driven underwriter discount in Rock (1986), platforms may preferentially allocate lower conditionally defaulting loans to *all* institutional investors to entice uninformed (less informed) institutional investors to continue to contribute capital in the presence of adverse selection. We show that platforms appear sensitive to these adverse selection issues and allocate loans with lower default rates to institutional investors when adverse selection is high.

Second, we entertain that the investment horizon of institutional investor participating in the whole loan markets may influence the platform's behavior. While some investors intend to retain loans on their balance sheet, other investors purchase loan assets to create a loan pool that is subsequently securitized leaving the institutional investor with little "skin in the game". Because of this, it's possible that ABS securitizers may be less sensitive to preferential allocation relative to balance sheet lenders. We show that during periods of heavy securitization, institutional investors are allocated loans with 5.3% higher conditional hazard rates than the retail (fractional) market while hazard rates of loans allocated to institutional investors are 7.8% lower than the retail (fractional) market during periods of securitization inactivity. Interestingly, these clientele effects appear to vanish following the enforcement of credit retention rules that drive platforms to package/issue ABS on their own.

Finally, we assume a blanket preference by the platform for institutional investors, assumedly because of their volume of capital available to fund loans. If platforms would preferentially allocate loans to institutional investors but are constrained by the attempt to maintain observably similar features between the fractional/whole loan markets, their freedom to assign may be limited. We show that the unevenness of capital provision, i.e. the fraction of volume that is distributed to retail/institutional investors, does not appear to constrain preferential allocation behavior.

By suggesting that the marketplace lending platforms have the ability to preferentially allocate loans, there is an embedded assumption that lending platforms have private information. While the loan platforms display a wealth of information on borrowers, the platforms are privy to an additional set of information associated with knowing the borrowers' identity. This enables access to additional factors such as geography, spending habits, or other data collected by third parties associated with identity.

Platform suggest that such information is used during the lending process and we view this as the likely source of their ability to preferentially allocate.

In examining FinTech platforms and their underwriting incentives, this paper connects the growing FinTech literature with the IPO literature on underwriter incentives. The literature on financial technology firms such as marketplace lending platforms is in its infancy but continues to expand. Early papers on marketplace lending focused on retail investor behavior during the period 2006 to 2013 when the majority of investors were retail investors on the platforms. These studies show that retail investors have a bias toward borrower profile beauty (Ravina, 2018), and geographic region (Hornuf and Schmitt, 2016; Lin and Viswanathan, 2015; Senney, 2016). They tended to herd with other investors (Zhang and Liu, 2012), and learn over time (Lin et al., 2015). Later work examines how platforms expanded over time (Havrylchyk et al., 2016) and if marketplace lending platforms substituted for commercial lending volume (Cornaggia et al., 2018; Tang, 2018). Our paper is unique in that it examines the incentives of marketplace lending platforms and abstracts from borrower behavior or the impact on credit markets.

In contrast to the growing FinTech literature, the IPO literature on underwriter incentives is a richly developed topic. Lowry et al. (2017) and Ritter et al. (2004) provide an excellent overview of the subject for the interested reader. Multiple factors may contribute to underwriter behavior (pricing/allocation), but we view three as predominant in the literature. The first is a group of models emphasizing moral hazard between issuers and investors/underwriters, the latter whom have a *quid pro quo* arrangement allowing underwriters to originate more securities (good and bad) in exchange for allocation/pricing (Goldstein et al., 2011; Loughran and Ritter, 2002; Reuter, 2006; Ritter and Zhang, 2007). Second, there are explanations using an information collection motive where investors are better informed on the value of the asset (Benveniste and Spindt, 1989; Sherman, 2000; Sherman and Titman, 2002) and preferential pricing/allocation is used to elicit information sharing. Finally, there are a group of theories that suggest issuing firms select underpricing in exchange for quality analyst coverage (Beatty and Welch, 1996; Loughran and Ritter, 2004), to signal firm quality (Welch, 1989), or to induce underwriter effort (Baron, 1982).

Our setting is most similar to the first (*quid pro quo*) channel where the platform may trade preferential allocation for capital commitments. However, it is also unique in that both the institutional and retail investor markets are competitive. Thus, while the marketplace lending platform can strategically allocate loans to a market, individual investors cannot be rewarded for information/additional services. Because the pricing of a debt contract is performed by the platform, the last channel motivated by borrowers (firms) inducing effort/favor from the underwriter would also appear irrelevant.

To our knowledge, there is little research that explores the incentive channels on FinTech platforms. The only exception to this is Vallee and Zeng (2018) and Venkatesan et al. (2018) who also examine the incentives of marketplace lending platforms. Vallee and Zeng (2018) examine how platform incentives influence a different outcome, namely the disclosure of information on prospective borrowers. Our paper is most similar to Venkatesan et al. (2018) who also focus on the incentives of marketplace lending platforms viewed through the lens of the equity underwriting literature. In contrast to our paper, their focus is on the pricing mechanism of the platforms and suggests that platforms discount security prices (increase loan interest rates) to allow broader participation of retail investors. Their results suggest this is only possible under a fixed pricing mechanism, compared to an auction pricing mechanism, which might explain why MLP's have evolved away from auction pricing mechanisms. We uniquely focus on loan allocation decisions and show a tension between multiple channels contributing to preferential allocation to investors.

1. Marketplace Lending Background

FinTech is a broad term that encompasses many financial intermediary steps including payment systems such as Bitcoin/blockchain, and asset creation technology such as marketplace lending or crowdfunding. Our study focuses on what is now known as marketplace lending which began in the

United States with the creation of LendingClub and Prosper mid-2000. These platforms originally provided simple debt contracts, i.e. personal term loans with no collateral. Over time, both platforms expanded into more complex loan contracts, such as automotive refinancing that involves collateral, and student loan refinancing which carries additional legal complexity. These platforms connected individual borrowers with retail investors that initially led the industry to be known as peer-to-peer (P2P) lending. This structure was maintained until 2012-2013 when LendingClub and Prosper began to adopt additional features to attract more institutional investor participation. For example, both platforms opened a second funding market dedicated to institutional investors in early 2013. With the inclusion of institutional investors who now dominate the capital supply, the process was renamed marketplace lending by most industry participants.

Other marketplace lending platforms emerged over time such as SoFi, Marcus, Funding Circle, and Upstart. The majority of these follow-on platforms rely solely on institutional investors for the supply of capital. The only platforms in the United States that included retail investors as capital suppliers were LendingClub and Prosper.[4] This would suggest that the allocation decision between retail and institutional investors is unique to these platforms, which is why we focus on them in the current study. However, other types of FinTech securities are emerging with broad retail investor participation, such as crowdfunded equity following the passage of Title IV of the JOBS Act (Regulation Crowdfunding). Currently, crowdfunding portals mix retail and institutional investors similar to the pre-2012 period for LendingClub and Prosper. However, as crowdfunding markets expand and draw additional institutional investor participation, it is possible for crowdfunding platforms (portals) to also segregate investors, forcing them to make similar allocation decisions.

Using technology, marketplace lending platforms have been able to “disintermediate” the traditional process of credit provision by allowing capital suppliers to selectively fund individual

[4] Note Funding Circle, which is a platform for small and medium-sized enterprise (SME) lending, also operates in the UK and provides retail investors access to fund loans. Until 2017, loans could be fractionally funded similar to the way LendingClub and Prosper operate in the US.

borrower credit demands. As a result, the platforms' process of credit provision is analogous to an underwriter brokering the offering of a new security. Here, the security is a debt contract issued by individuals and initially offered to investors. We describe some of the mechanics of marketplace lending below and review some of the structural features that allow us to examine platform allocation behavior.

We present an overview of the marketplace lending process in Figure 1. As shown there, marketplace lending platforms offer individual borrowers the ability to apply for credit online. Borrowers provide basic information on income, location, and their social security number so that the platform can pull their credit profile. The platforms screen credit applications using this hard information without incorporating additional soft information, such as extenuating circumstances affecting their credit history that could be obtained through borrower conversation with a loan officer. After passing the initial credit screening, the borrower's loan request is listed in an active funding market or allocated to a passive funding pool. Within the active funding markets, the platform then makes a second allocation decision to list a loan request in either the fractional (retail) funding market or the institutional (whole) funding market. This second allocation decision is the focus of our study.

Prior to 2012, LendingClub and Prosper had only one active funding market and a passive funding pool. In this early period, most investors were retail investors, and the platforms allowed active investors to fractionally fund loans in $25 increments. The process was competitive, and as institutional investor participation increased in 2012, it became increasingly hard for retail investors to compete against automated investment tools implemented by institutional investors. Recognizing the opportunity for expansion, both platforms opened a second actively funded market for institutional investors to fund loans. This second market required investors to fund loans in their entirety and is known as the whole loan market. As a result of this two-market structure, the platforms were forced to make an allocation decision between the markets. That is, the platforms choose whether to place a borrower loan request in the whole loan market for institutional investors to fund or the fractional loan market for retail investors to fund. Currently, the platforms state that the allocation of loans is random between these markets.[5]

In some cases, the platforms allow unfunded loans in one active funding market to "roll over" into the other active funding market (See Figure 1 item (4)). The amount of time a loan is available to be actively funded varies from platform to platform and between the whole loan market and the fractional market. In general, institutional (whole loan) markets have 1-24 hours to fund loans before they roll over, while retail (fractional) investors have 7-10 days. This practice occurs with both LendingClub and Prosper but also on other platforms like Funding Circle (Mohammadi and Shafi, 2017).

The alternative allocation for platforms is a passive funding pool (Figure 1 item (2)), where loans are earmarked to fulfill long-term agreements between the platforms and institutional investors or pooled for passive funding vehicles offered by the platform to investors. Sometimes the platforms select loans based on criteria for particular institutional investors but not in all cases. For example, Prosper signed a long-term loan agreement with a consortium of hedge funds to purchase $5 billion in loans over a two-year period beginning in 2017. Loans for this agreement are not selected out of the active funding market but rather set aside in a passive funding pool. Other platforms, such as Upstart, operate exclusively through passive funding pools but do not allow investors to specify any selection criteria.

2. Hypothesis Development

In the equity IPO literature asset allocation is one way of rewarding investors for providing costly information to underwriters (Aggarwal et al., 2002; Goldstein et al., 2011) to more accurately price the asset. While marketplace platforms price the debt contracts independent of institutional information, they are still driven by origination volume. Thus, marketplace platforms may use preferential allocation as a tool to draw larger institutional investors to fund loans even absent the information revelation channel. This suggests our first two testable hypotheses:

---

[5] https://help.lendingclub.com/hc/en-us/articles/115009000328-How-LendingClub-balances-different-investors-on-its-platform , https://www.sec.gov/Archives/edgar/data/1416265/000156459016015019/prosper-10k_20151231.htm

Hypothesis 1. *If loans are randomly allocated between the active whole loan market and fractional retail market, the hazard rate for default will not depend on market allocation ($H1_0$) ceteris paribus. Alternatively, if platforms allocate loans non-randomly, the default hazard rate might be different for loans assigned to the two markets ($H1_A$).*

Hypothesis 2. *If loans are randomly allocated between the active whole loan market and fractional retail market, the hazard rate for prepayment will not depend on market allocation ($H2_0$) ceteris paribus. Alternatively, if platforms allocate loans non-randomly, the prepayment hazard rate might be different for loans assigned to the two markets ($H2_A$).*

Assuming platforms preferentially allocate loans, it is possible that multiple channels may drive such behavior. Similar to the Rock (1986) model of security issuance, the platforms may resolve adverse selection problems through preferential treatment. In the Rock (1986) model, underwriters provide a security discount to encourage participation in the funding process when capital providers are subject to adverse selection. While our focus in the current paper is not on the pricing of securities, we do verify that loan contracts assigned to retail and whole loan participants are similarly priced based on loan/borrower details. As an alternative to a pricing discount, it is possible that platforms preferentially allocate loans to active funding markets with high adverse selection. More formally:

Hypothesis 3. *If adverse selection is high within an active funding market, the marketplace lending platform will allocate loans with lower expected default ($H3_0$) to that active funding market ceteris paribus. Alternatively, the platform allocation will not depend on adverse selection ($H3_A$).*

Another possible channel that may drive allocation behavior of the platform is the type of institutional investor funding the primary issuance of the loans. While some institutional investors on the platform may be buy-and-hold investors who intend to retain the loan on their balance sheet, other institutional investors pool loans and securitize them into asset backed securities. Buy-and-hold investors will inherently suffer losses from loan default and have incentives to ensure the quality of loan received in the primary note offering. However, institutions that securitize the loans may not hold any exposure to the notes after securitization, i.e. any "skin in the game" (Rajan et al., 2010), and may be willing to forego costly monitoring/analysis. Thus, the platforms' need to preferentially allocate because of adverse selection issues in an active funding market may be driven by clientele effects such as the type of institutional investor. Given a measure of the fraction of securitization activity being funded:

Hypothesis 4. *If securitization activity is low within an active funding market, the marketplace lending platform will allocate loans with lower expected default ($H4_0$) to that active funding market ceteris paribus. Alternatively, the platform allocation will not depend on securitization activity ($H4_A$).*

Finally, while platforms may prefer to preferentially allocate loans to certain participants, constraints may arise that prevent preferential allocation if platforms attempt to maintain certain observable characteristics between active funding markets. For example, if a large portion of loans within a particular credit grade and loan term are allocated to one active funding market because of investor preference, it may be impossible for a platform to preferentially allocate loans if it attempts to maintain similar observable characteristics like average credit score. In this vein, we formally test the platforms' freedom to preferentially assign loans:

Hypothesis 5. *If the capital supplied by investors to active markets is too uneven, the marketplace lending platform will allocate loans with similar expected default to active funding markets ($H5_0$) ceteris paribus. Alternatively, the platform will allocate loans with a lower expected default to a particular active funding market ($H5_A$).*

3. Sample and Variable Construction

Our sample is composed of all the loans originated in the whole loan market and fractional market on the lending platform LendingClub, for the period 9/21/14 through 2016, and Prosper, for the period 3/25/13 through 2017.[6] We gather multiple data sets from each platform. First, the platforms provide a loan issuance file that includes details on the borrower's credit profile and loan details at the time the loan is originated. Both platforms identify the initial funding market (fractional, whole) where

[6] This encompasses all the loans that originated on Prosper. LendingClub has an additional private market for institutional investors to actively fund subprime loans. The data for these loans are not publically available.

the loan is listed, and we present the summary statistics for the two loan markets based on the initial listing status in Table 1. In Panel A, we present the mean and standard deviation for LendingClub loans in the fractional and whole loan markets. Panel B reports similar statistics for Prosper loans separated by funding market.

From the platform files, we gather borrower credit information, number of inquiries in the past six months, the number of years since first credit is established, credit line utilization, and debt-to-income of the borrower, and employment length. The platform files capture loan details: the amount requested by the borrower, interest rate assigned by the platform to the loan, platform credit rating, term, and loan purpose. We also gather information on the initial allocation of a loan as whole/fractional from the platform data. In the case of Prosper, we are able to observe if a loan is sold in the whole loan market and the timestamp associated with its sale in the whole loan market. For the Prosper platform, we use this to identify loans that rollover from the whole loan market to the fractional market (Figure 1 item (4)).[7]

In order to identify rollover loans for LendingClub, we augment details of the loan contracts provided by LendingClub with information publically available through the Security and Exchange Commission's (SEC) EDGAR database. LendingClub loans are filed with the SEC to provide the public with a source of information on the potential investment. Initially, the platform submits loans to the SEC when the borrower's loan request has passed the platform's initial credit screen and the loan is *listed* for funding in one of the marketplaces (see Figure 1). We collect data from the SEC on loans listed for funding and match that to the data provided by the platform. This provides some loan details that are omitted from the platform data such as the date of listing/origination.[8] The platforms also file a second registration update with the SEC for the loans that are successfully funded through the retail active market (Figure 1 item (5)). The platforms are only required to file an update for loans that fractional investors fund. Using the registration updates of fractional market *sold* loans, we can distinguish between loans that are initially assigned and funded in the whole loan market (Figure 1 item (3)) versus loans that are

[7] Loans that are initially allocated to the whole loan market but have no whole loan sale timestamp are assumed to rollover to the fractional market.
[8] LendingClub only provides the month of origination in the files available through the platform

initially assigned to the whole loan market but roll over and are funded in the fractional market (Figure 1 item (4)).[9]

The second set of data obtained from the platforms is loan outcome data. LendingClub provides historical data on loan outcomes, which allows us to track the monthly progress of a loan and determine its current/final status (default, prepaid, current, complete/matured) and length of survival. Prosper provides information about the loan's outcome up to the date of data download. In order to estimate the outcome status and months of survival of the loan, we use the dollar amount of interest paid in combination with the loan term and interest rate to estimate the loan status and survival time.[10] We verify the validity of this approach using a previously available loan outcome file and find it to be a good approximation of loan outcome and survival.[11]

Marketplace lending loans are often funded by banks or hedge funds and securitized into an asset-backed security (ABS). We gather securitization data from multiple sources to later test our hypothesis (H4) on allocation incentives. Our initial list of ABSs comes from PeerIQ's quarterly report on marketplace lending securitization. PeerIQ publishes securitization information on multiple consumer loan types (student, personal, small and medium-sized enterprise, etc.). Their report includes the ABS issuer, loan originator, and information about the ABS issue (size, coupon, credit rating, etc.). We limit their list to ABSs issued with consumer loans as the asset pool. We then match the ABS data with information from the Kroll bond rating agency to obtain additional information on the ABS. Critically, we collect the statistical cutoff date that approximates the last day that assets are added to the ABS pool and the average age of the loans on that date. For issues not rated by Kroll, we reference Bloomberg for the average loan age at issuance and impute the average time between the statistical cutoff date and ABS

[9] An insignificant amount of loans that fail to be funded in the fractional market and are rolled over to the whole loan market. We estimate that 1.34% of loans fall into this category, which are omitted from the sample.

[10] Prosper loans are fixed-rate amortized term loans, which allows us to approximate the survival time of the loans by the amount of interest paid.

[11] Prosper previously licensed a loan outcome file for academic research that contained the monthly status of loans similar to the file available by LendingClub. Prosper discontinued our licensing of this data in January 2018. However, we were able to verify the rate of classification, which correctly typed loan status for 94-99% of loans (depending on loan outcome). We also estimated the average difference in loan survival time between the two approaches at 6.4 days.

issue date (24.7 days). This methodology allows us to estimate when loans included in the pool were likely to be originated. Using this information, we calculate the quarterly origination activity driven by securitization purchases. Figure 2 presents a summary of the securitization activity by platform over the sample period.

In Table 1 Panel A, the summary statistics for the loan data on LendingClub reveal noticeable differences in borrower characteristics between the two markets. In Panel B, the difference between the two markets is also visible for Prosper. Figure 3 compares default rates for LendingClub and Prosper by grade across the two active funding markets. Figure 4 compares prepayment rates for LendingClub and Prosper by credit grade and funding market. In unreported results, we formally compare the default rate and prepayment rate for each funding market (fractional/whole) by grade and find the difference between default rates and prepayment rates are statistically significant on LendingClub at the 1% level of significance for loans in the B, C, and D credit grades. We find no difference in the average default/prepayment rates between the two markets (fractional/whole) across credit grades for Prosper.

Figure 3 and 4 are suggestive of non-random allocation on the part of the LendingClub platform. It is possible that other loan/borrower characteristics influence the conditional default rate outside of the information contained in the credit grade. The information implied in the credit grade may also be time-variant. As shown in Figure 5, the fraction of loans within each credit grade assigned to the two markets varies considerably. For example, in 2014, approximately 44.4% of the A grade loans on LendingClub are assigned to the fractional market compared to 52.6% of the G grade loans. These differences widen over time and by 2016, only 16.25% of the A grade loans are initially assigned to the fractional market while 49.3% of the G grade loans are assigned to the fractional market. We see a similar trend for Prosper loans in Figure 5. In the next section, we formally test the difference in loan outcomes in a multivariate setting to address such concerns.

4.1 Empirical Results

Our first objective is to test the assertion that loans are randomly assigned between the two active markets on LendingClub and Prosper. We begin by examining how loan outcomes such as default and prepayment are associated with allocation decisions by the platforms. We emphasize that our goal in this context is to demonstrate an *association* between default/prepayment and the allocation of the loans instead of a causal relationship. Such an association should be sufficient to challenge the notion that loans are randomly allocated between the active markets. In Section 5, we attempt to show channels that cause differences in allocation.

Figure 3 Panel A suggests that LendingClub selectively allocates loans with lower ex-post default rates to the institutional (whole loan) market even after controlling for loan credit grade. However, if borrower default risk is time-varying due to the economic environment, and the proportion of observations in a particular credit risk category are not evenly spread out over time, it is possible that differences in the average default could be explained by such time-series effects. Other loan or borrower characteristics may also influence credit risk outside of loan rating. Thus, it is important to address such econometric concerns in a multivariate setting.

Beginning with the LendingClub analysis, our loan data runs from third quarter 2014 through 2016.[12] Because the term of the loans that originated on the platform is either three years or five years, none of the loans in the sample will have the ability to mature, and our pool of observations will be right truncated on our variables of interest (default, prepayment). To address such truncation, we estimate a hazard model for the loans (Billett et al., 2011; Lin et al., 2013; Meyer, 1990). This allows us to compare the default and prepayment likelihood for the active funding markets given the status of the loans when we collect the loan data.

We include multiple borrower characteristics such as the number of inquiries in the last six months, years since credit was established, indicators on debt-to-income quartile, indicators on loan purpose, and credit utilization at the time of listing. We follow Lin and Viswanathan (2015) by

[12] Note that prior to 9/21/14, when LendingClub made loans available to be funded in the active whole loan market, the data provided by the platform does not indicate which loans were initially assigned to the whole/fractional market. Our sample begins in late 2014 when this indicator was consistently included.

incorporating the square of credit utilization. The specification also uses additional information on loan contract features to describe the risk of default (prepayment). We also include the dollar amount of the loan request in addition to the interest rate on the loan, an indicator for the term of the loan, the textual length of the borrower's loan request description, and also indicators for the credit grade of the loan assigned by the platform. Additionally, the specification uses a squared interest rate term to account for the potential nonlinear influence of interest rates. To adjust for the variability of credit risk due to the macroeconomy, we incorporate year-quarter fixed effects.

Implicitly, supply-side characteristics such as an identifier for the active market (whole or fractional) should not be associated with the default of the loans available to be funded if loans are randomly allocated and borrower-risk characteristics are identified. However, to test Hypothesis 1 we include an indicator equal to one if the loan is initially assigned to the whole loan market. In summary,

$$h(t|x) = h_0(t)\, exp(x\beta) \tag{1}$$

our specification for this test is:

where initially h(t|x) is the hazard rate of default, i.e., the conditional default rate, and

$$x\beta = \beta_t + \beta_1 \cdot Whole_{i,t} + x'_{platform}\beta_p + x'_{borrower}\beta_c + x'_{loan}\beta_l + \epsilon_{i,t}\ .$$

We report the results of Equation 1 in Table 3 columns (1)-(3). Column (1) reports the results for the full sample of loans while columns (2) and (3) split the sample into investment grade (grades A, B, C) and high yield (grades D, E, F, G) loans respectively. The table reports the exponential form of the coefficients, i.e. the hazard ratio, for each of the variables. Hazard ratios greater than one suggest the variables have a positive association with default while ratios less than one have a negative association with default. In column (1), the hazard ratio for *Whole* suggests that loans allocated to the institutional market have a 3.1% lower conditional default rate (1-0.969 =0.031 or 3.1%) than loans assigned to the retail market even after controlling for the riskiness of the loan/borrower. If the average conditional default rate for loans allocated to the fractional market on LendingClub is 9.75%, this suggests that loans allocated to the institutional investor market have an average conditional default rate of 9.44% (9.75% * 0.969 = 9.44%). The effect appears to be driven by the riskier high yield loans in column (3). The hazard ratio for high yield loans in the whole loan market is 4.9% lower than loans in the fractional market. The coefficient for the whole market indicator is statistically insignificant for the investment grade loans in column (2). Based on the results from this specification, we reject the null for Hypothesis 1 that loans are randomly allocated across the active funding markets on the LendingClub platform.

Looking at the other variables in the specification, the hazard ratios are greater than one for credit inquiries, larger loan amounts, and loans with higher interest rates. Longer term loans have a hazard ratio of less than one while credit line utilization has a nonlinear impact on the likelihood of default.

We also investigate the likelihood of prepayment across the two active markets. Hypothesis 2 suggests that under random allocation, there should be no difference in the likelihood of prepayment across the two markets. We again estimate the conditional hazard rate with loans now exiting the sample because of prepayment. Results are located in Table 3 columns (4)-(6). The hazard ratios are reported for the full sample in column (4) and the subsamples based on credit grade in columns (5) and (6). According to the results in column (4), loans assigned to the whole loan market have a lower probability of prepayment. This appears to be driven by the investment grade segment in column (5). Column (4) suggests that loans assigned to the institutional market have a 1.3% lower conditional prepayment rate. This translates to a conditional prepayment rate of 18.67% relative to a baseline conditional prepayment rate of 18.92% for retail investors. Thus, we reject the null for Hypothesis 2 that loan prepayment is similar for the two active funding markets on the LendingClub platform.

After providing evidence that LendingClub loans are non-randomly allocated, we turn our attention to the Prosper active markets. We again use loan-level data, this time from the Prosper platform. We estimate the default and prepayment hazard rates again using Equation 1.

The results for loan default are reported in Table 4 columns (1) - (3). Again, we report the aggregate sample in column (1) and the investment grade (grade AA, A, B) and high-yield loans (grades C, D, E, HR) in columns (2) and (3) respectively. The hazard ratio in the aggregate sample for *Whole* is statistically insignificant, indicating no allocation differences on the part of Prosper. After splitting the sample by credit risk, we see evidence of higher defaulting loans allocated to the whole loan platform for investment-grade loans and no evidence of allocation differences in the high-yield loans. Prepayment results in columns (4) – (6) suggest whole loan investors receive loans with similar prepayment rates. In summary, the Prosper platform shows little to no evidence of preferential assignment to the institutional investors. If anything, it would appear institutional investors on the Prosper platform are allocated worse loans for the investment grade segment. Thus for the case of Prosper, we also reject the null for Hypothesis 1 but fail to reject the null for Hypothesis 2.

4.2 Robustness Tests

Table 3 presents results for LendingClub assignment behavior over the entire sample period. Based on the results in Table 3, it appears that LendingClub preferentially allocates loans to the institutional investor market (active whole loan) while Prosper may preferentially allocate loans to retail investors. However, midway through the LendingClub sample, the founding CEO, Renaud Laplanche, was forced to resign in May 2016 due to multiple managerial issues.[13]

Following the May 2016 announcement, many investors temporarily withdrew funding from the platform. This withdrawal of funding peaked in June 2016 when LendingClub funded over $25 million in loans directly because of the lack of institutional funding. We also observe a permanent shift in the rollover ratio, as shown in Figure 6 suggesting other changes in the allocation behavior of the platform. In order to court institutional investors to return to funding loans, LendingClub increased interest rates an average of 55 BPS and tightened credit screening requirements on debt-to-income. It is possible the preferential allocation observed in Table 3 is driven by early management decisions and was corrected following Laplanche's replacement. However, it is also possible that the allocation behavior may be a result of the platform's desperation for capital following the managerial change. If either is the case, the

[13] Laplanche was forced to exit because of a failure to disclose some conflicts of interest around his material stake in a company doing business with LendingClub. He was also found to be responsible for altering data on a group of loans sold to a large institutional investor, Jefferies, so that the loans could meet their purchasing criteria.

changes in preferential allocation may be driven by a portion of the sample even after controlling for time effects using year-quarter dummies.

To examine this issue, we divide our loan sample around May 2016 when the senior management restructuring occurs and repeat the analysis from Equation 1. Results for loan default are displayed in Table 5 panel A and prepayment in panel B. In the period leading up to 2016 Q2, we continue to see evidence of preferential allocation in loan default measures. The results shown in Table 5 Panel A columns (1) and (3) closely match the aggregate results in Table 3. In columns (4) and (6) we see the preferential allocation strengthens in the latter part of the sample. Loan defaults for the institutional market are substantially lower following the management changes in 2016. In panel B, there is a similar increase in institutional preference. In the period leading up to 2016 Q2, we see prepayment hazard ratios appear identical between the fractional and whole loan markets, but following the managerial change in 2016, the active institutional market appears to receive loans with a lower prepayment rate. Again the results are stronger in the high-yield (riskier) credit grades but appear in both credit risk segments.

The results in Table 5 suggest the organizational change in May 2016 appears to have had a significant influence on platform allocation behavior. We speculate that this may be due to a renewed reliance on institutional investor capital. The sudden drop in borrower demand following the Laplanche resignation was reversed relatively quickly, but the institutional capital was much slower to return. We view the majority of platform action in that time period (interest rate increase, screening contractions, and direct purchasing activity) as an attempt to draw institutional investors back to the platform. Based on the results, it is likely preferential allocation may be another tool of the platform to encourage institutional participation. While the results in Table 5 do suggest an intensifying of preference following the managerial shift, there is still evidence of platform preferential allocation prior to the change.

Two additional econometric issues could potentially arise in the analysis. First, while we follow the extant literature (Lin et al., 2013) and separate prepayment activity from default activity, it is possible the allocation decision by the platform is made simultaneously on both loan outcomes. Said differently, a platform that preferentially allocates loans based on default may unintentionally assign lower prepayment rate loans because of the default/prepayment dependency (and vice versa). If this is the case, it is possible the models presented earlier are potentially biased (Roberts and Whited, 2011).

To show that the results do not appear to be driven by such issues, we employ a more parametric approach that allows us to model such a dependency. Specifically, we use a frailty model that assumes a gamma distributed baseline hazard and use maximum likelihood estimation to simultaneously consider default and prepayment exit events. We divide the sample for LendingClub into the early/later periods similar to the analysis in Table 5 and for Prosper, we divide the sample yearly to aid in estimation.

We report the LendingClub *coefficient* estimates in Table 6 and Prosper coefficient estimates in Table 7. In the LendingClub test in Table 6, the coefficient on *Whole* is negative and statistically significant for both exit events (default and prepayment) and in both periods. Thus it is unlikely the LendingClub results in Tables 3 or 5 are driven by such a joint dependency. Turing to Table 7, the results for Prosper show that the coefficient on *Whole* does not appear to be significant in any of the five specifications. The results for prepayment also appear to be similar to Table 4 with 3 out of the five years appearing statistically insignificant while the other two years are significant at only the 10% level.

The second potential econometric issue is that we only observe outcomes for a portion of the loan demand. This could arise because the platform screens the initial application pool but also because investors only fund a portion of the loans presented on the platform. In the case of the LendingClub platform, we are able to avoid the latter selection issue because all loans passing the initial platform credit screen are offered funding.[14] Loans that are rejected by both active markets are backstopped by the platform and so all loan outcomes are observed. However, as described in Heckman (1979), the former selection issue can potentially bias our estimation efforts.

Heckman (1979) suggests that one way to obtain unbiased coefficient estimates in the analysis would be to include the linear terms of the selection equation in the outcome model if the selection equation can be well approximated by the linear terms of its Taylor series expansion. The downside to this approach is that variables included in the outcome model can appear to determine the loan outcome

[14] We confirm this 100% funding rate with LendingClub.

(default, prepayment) when in reality they drive the selection equation. In our scenario, this would be acceptable if we can exclude our variable of interest, *Whole*, from such concern. Because the assignment of the loan follows the platforms decision to screen, we view the loan level allocation decision as unlikely to drive the screening decision. Thus by including parameters for the screening decision in the loan outcome equation, we should be able to estimate an unbiased coefficient for our variable of interest in the loan outcome model. Thankfully, the platforms suggest clear screening parameters such as a credit score cutoff of 640 and debt-to-income restrictions of 35-40%. We include these terms in the outcome equation and report the results in Table 8 columns (1)-(2) for the default model and column (3)-(4) for prepayment. We include the additional screening variable *RiskScore*, the borrower's credit score, which the platforms report is incorporated into the screening process. The results in columns (1) and (2) are similar in magnitude and statistical significance to the results in Table 3 suggesting selection is not likely to bias the main results.

5. Channel Exploration

In the previous section, we demonstrate that one platform (LendingClub) appears to preferentially allocate loans to institutional investors while the other (Prosper) allocates loans with loer hazard rates to retail investors. From the IPO literature, it is not surprising that an underwriter might preferentially allocate loans to institutional investors (Aggarwal et al., 2002). Yet, the typical motives for allocation are less straightforward in marketplace lending. Because the active funding markets are competitive and platform allocation only occurs at the market level, not the individual investor level, the platform has no ability to compel "moral suasion" on the part of the investor. In similar fashion, the literature tells us that loan originators with little exposure to loan performance, i.e. "skin in the game", may be willing to originate lower quality loans when their incentives align with such activity (Rajan et al., 2015). Such aligned incentives may explain Prosper's willingness to allocate loans with higher default hazards to institutional investors. In this section, we explore channels that may drive the allocation decision in marketplace lending.

We consider three, non-mutually exclusive channels that could explain allocation behavior observed in the previous section. In the first channel, we investigate if differences in adverse selection within the whole loan market may drive allocation. It is possible some institutional investors generate costly private information to better select loans while others rely on public signals such as credit score (Rajan et al., 2010). Thus, privately informed lenders may generate adverse selection issues for other institutional investors in the whole loan market. Similar in spirit to the Rock (1986) underwriting model, the platforms may choose to preferentially allocate loans to *all* institutional investors to retain uninformed (publicly informed) investors in the whole loan market. If allocation behavior varies during periods of high/low adverse selection, it is suggestive of an *Adverse Selection* channel.[15]

To test the adverse selection channel, we need to construct a measure of adverse selection within the institutional investor market. To do this, we use the LendingClub platform loans around the time of the Laplanche resignation. As mentioned in the robustness section and shown in Figure 5, loans that are unfunded on LendingClub's whole loan market roll over to the fractional market. In the period prior to the resignation, the rollover rate ranges from 0%-67%. A high rollover ratio could be driven by changes in demand for loans or the supply of capital for loans. For example, if a temporary spike in credit demand from poor quality borrowers were to pass through the credit screen of the platform and be allocated to the whole loan investors, assuming they are informed the investors would avoid such loans and allow them to rollover. If the rollover ratio is demand driven we would expect to observe higher ex-post default among the rollover loans similar to a winner's curse when the rollover ratio is high. However, if the rollover of loans from the institutional market is driven by capital supply fluctuations, a high rollover ratio would be more representative of the loan quality allocated to the institutional market on average, and a low rollover ratio would indicate intense competition among capital suppliers and suggest a winner's curse when the

[15] We assume that retail investors would find it unprofitable to expend a similar effort to generate private information because of investment caps (per loan) in the fractional market. For example, if investors are capped at investment volumes of 10% the loan amount, generating private information for loans may be too costly relative to the investment size.

rollover ratio is low. If this is the case, we will observe higher ex-post default among the rollover loans when the rollover ratio is low.

We test this assertion first in Table 9 by looking at the quality of loans rolling over from the institutional market into the fractional market. Specifically, we substitute the exponential term in Equation 1 with:

$$x\beta = \beta_t + \beta_1 \cdot W/W_{i,t} + \beta_2 \cdot W/F_{i,t} + \beta_3 \cdot HighRollover_t + \beta_4 \cdot W/F_{i,t} * HighRollover_t$$
$$+ x'_{platform}\beta_p + x'_{borrower}\beta_c + x'_{loan}\beta_l + \epsilon_{i,t}$$

where *W/F* indicates loans that are allocated to the whole loan market but roll over and are funded in the fractional market. Similarly, *W/W* indicates loans initially allocated to the whole loan market that are funded by the whole loan investors. The specification uses a base of loans that are allocated to the fractional market and funded in the fractional market. The variable *HighRollover* is an indicator equal to one if the rollover ratio is larger than its median.

The results in Column (1) and (3) of Table 9 show the hazard ratio on *W/W* is less than one and statistically significant at the 1% level which suggests institutional investors fund loans with lower default than fractionally allocated and funded loans (F/F base hazard). This could be because of private information (skill), preferential allocation, or both. Looking at the loans that are allocated to the whole market but roll over, *W/F*, we see that on average these loans default at a rate similar to the fractionally funded loans in column (1) or at a higher rate in column (3) when the rollover ratio is low (the hazard rate is above 1.0). However, when the rollover ratio is high, the interaction between *W/F* and *HighRollover* indicates these loans have lower conditional default rates than the fractionally funded loans. This suggests that fluctuations in the rollover ratio are likely driven by capital suppliers and adverse selection is likely to be high when the rollover ratio is low.

Using the rollover ratio as our measure of adverse selection, we now return to the allocation choice of the platform. Looking again at the allocation of loans to the whole (fractional) market, we include the lagged rollover ratio in the earlier specification and its interaction with the whole loan market indicator. Using the lagged indicator helps avoid any look-ahead bias. The results are reported in Table 10. The results shows that the lagged rollover ratio coefficient is significantly larger than one but statistically insignificant. This suggests that adverse selection issues in the whole loan market, do not appear to significantly impact the default rate of the retail investors. However, when the rollover rate is high, adverse selection issues are minimal and the platform allocates loans with a higher ex-post default rate to the whole loan market. The greater than one hazard rate on the interaction term implies that when adverse selection is most severe, the platform will assign a lower ex-post defaulting loan to the whole loan market. These results are consistent with the null hypothesis $H3_0$.

The second channel we deem as the *Clientele* channel recognizes that two distinct types of institutional investors purchase whole loans from the platforms. Marketplace lending platforms have drawn both balance sheet lenders, who purchase loans with the intent to hold the loan as an asset, and financial firms, who purchase loans and then securitize pools of loans to issue asset-backed securities (ABS). Balance sheet lenders like commercial banks have clear incentives to acquire lower defaulting loans (relative to their price) and would benefit from preferential allocation by a platform. ABS issuers, on the other hand, might retain such a small position in the ABS that preferential allocation is less beneficial. If this is the case, one may expect to see less preferential allocation on platforms when ABS issuers' securitization activity is high.

There are noticeable differences in institutional investor composition between the two platforms. Namely, outside ABS issuer participation was exceptionally heavy on the Prosper platform until 2016 Q2 while LendingClub institutional investors were primarily balance sheet lenders (buy and hold) during that period. Additionally, securitization volume backed by platform loans has been volatile over the time series (Figure 2). Credit retention rules from the Dodd-Frank Act became effective in December of 2016 requiring ABS issuers to retain at least 5% of an ABS issue. Since the effective date of the credit retention rule, only one outside financial firm has issued one ABS securitized by loans from the platforms. To maintain origination volume, the platforms began issuing their own ABS backed by platform loans in 2017.

If preferential allocation is driven by clientele effects, we should be able to use the variability in securitization activity to show periods of low securitization causes platforms to preferentially allocate loans to institutional investors while periods of high securitization activity may cause platforms to allow lower quality loans to enter the funding markets to satiate ABS investors. We repeat the default analysis from Equation 1 for the Prosper platform, including an indicator for the securitization quiet period (2016 Q2 – 2016 Q4) and an interaction term with the whole loan market indicator. The results are reported in Table 11.

Similar to the results in Table 4, the aggregate sample analysis in Table 11 column (1) hazard ratio suggests that institutional investors receive a worse allocation on average. The hazard ratio on *Whole* is 1.052 suggesting a 5.2% higher conditional hazard rate for the whole loans assigned to institutional investors when securitization activity is occurring. However, when we include the securitization lull indicator (*Quiet*), the picture begins to change. The hazard ratio for *Quiet* is statistically insignificant while its interaction with the *Whole* indicator is 0.877 and statistically significant. This suggests that when there is no securitization activity, the institutional investors in the whole loan market are allocated loans with a 7.7% (1- 1.052*0.877 = 0.077) lower conditional default rate. Thus we fail to reject the null hypothesis $H4_0$. In column (2) we restrict the sample to loans prior to 2017Q2 and use only the period up to 2016 Q2 as the securitization activity and observe results similar to the full sample. However, when we restrict the sample to loans after 2016 Q1, when the platforms are selecting loans for securitization, column (3) suggests institutional investors are no longer allocated loans with a higher conditional default rate and securitization activity has no influence on the quality of loan allocated to other institutional investors. These results suggest that the type of institutional investor matters to the platform and preferential allocation depends on clientele effects. It also is suggestive that the position of the ABS issuer, outside of the platform versus inside the platform, matters for loan quality on the platform.

In the final channel, we naively assume that platforms have a preference for all institutional investors potentially because of their ability to provide more origination capital. This would be similar to the quid pro quo arrangements in the IPO underwriting literature (Goldstein et al., 2011). However, it may only be possible to preferentially allocate loans to institutional investors if the supply of capital in the fractional market is large enough to disperse lower quality loans. As we saw in Figure 4, institutional and retail investors appear to have different appetites for risk; retail investors are assigned a much larger fraction of the high-risk loans on both platforms. In the figure, we see that the fraction of retail funding is particularly lopsided for Prosper with less than 10% of the capital originating from retail investors in most credit grades by 2017. Under the *Freedom to Assign* channel, all platforms will preferentially allocate to the institutional market if the fraction of retail funding in a credit grade is high and not constraining.

We test this channel in Table 12 using two proxies for constraints on the freedom to assign. In columns (1)-(3) we include *FracPercent*, the weekly percentage of loans assigned to the retail investors in loan *i*'s credit grade, which is subsumed in the year-quarter fixed effect. The interaction of *FracPercent* with *Whole* in columns (1)-(3) is statistically insignificant suggesting the platforms are not constrained by the freedom to assign higher quality loans to the institutional market. In columns (4)-(6) we use an alternative proxy for the constraint, *HighFreedom*, which indicates that the fraction assigned to retail investors is larger than the first quartile in that credit grade. However, again the hazard ratios for *HighFreedom* and its interaction with *Whole* are not statistically different than one suggesting no difference from the baseline hazard rate. The results from Table 11 are most consistent with the null hypothesis $H5_0$ .that suggests platform allocation is constrained by investor composition (retail/institutional).

6. Conclusion

We investigate the assertion that marketplace lending platforms randomly allocate loans between institutional and retail markets. In the first portion of the paper, we show that on average, one platform preferentially allocates loans to institutional investors while the other platform preferentially allocates loans to retail investors. We find that loans allocated to the active institutional market on LendingClub have a conditional default (prepayment) rate that is 3.1% (1.3%) lower than the retail funding market. In a similar exercise, we find that Prosper allocates investment grade loans with a 7.1% higher hazard rate to institutional investors.

These baseline results are robust to multiple econometric concerns. We show that the preferential allocation is not driven by a particular management group on LendingClub. Additionally, after incorporating a Heckman selection step into the survival model, the results do not appear to be driven by selection induced bias. Finally, we estimate simultaneous exit models to show our initial findings are not an artifact of the dependency between default and prepayment.

After providing evidence of preferential allocation behavior by platforms, we delve into potential channels describing the platform behavior. We examine three channels, the adverse selection, clientele, and freedom to assign channels. Our results indicate that both adverse selection and clientele effects appear to drive platform behavior.

We show that adverse selection problems likely exist within the institutional funding market among institutional investors on the LendingClub platform. Using the lagged rollover rate as a proxy for adverse selection, the platform appears to vary allocation preference with adverse selection. When adverse selection is high, the platform appears to allocate lower expected default loans to the institutional market. This suggests the platform is using allocation to alleviate the Rock (1986) winners curse in the whole loan market.

In the clientele channel, institutional investor type may drive platform allocation. Consistent with the originate to distribute literature (Rajan et al., 2010), we find preferential allocation to institutional investors on the Prosper platform when securitization activity is absent but allocation favors retail investors when securitization activity is heavy. Presumably, institutional investors, securitizing loans retain little of the ABS issue allowing the platform to favor the buy and hold activity of retail investors or possibly stretch credit screening hurdles to provide enough volume to satisfy ABS investor demand. Interestingly, preferential allocation appears to be absent following the Dodd-Frank credit retention rule enforcement when platforms took over the role of securitization issuance.

Our results suggest incentives among marketplace lending platforms matter and that allocation by the platforms mirrors IPO underwriter behavior in some aspects. Given the growth in size and scope of the marketplace lending platforms and the wide use of technology in other areas of capital intermediation like crowdfunding and initial coin offerings, our results suggest the need for a more careful understanding of platform incentives. Policymakers should consider the incentives created by the use of new technology in capital markets and how best to disclose such incentives to protect retail investors.

References

Aggarwal, R., Prabhala, N.R., Puri, M., 2002. Institutional allocation in initial public offerings: Empirical evidence. The Journal of Finance 57, 1421–1442.

Baron, D.P., 1982. A model of the demand for investment banking advising and distribution services for new issues. The Journal of Finance 37, 955–976.

Beatty, R.P., Welch, I., 1996. Issuer expenses and legal liability in initial public offerings. The Journal of Law and Economics 39, 545–602.

Benveniste, L.M., Spindt, P.A., 1989. How investment bankers determine the offer price and allocation of new issues. Journal of Financial Economics 24, 343–361.

Billett, M.T., Garfinkel, J.A., Jiang, Y., 2011. The influence of governance on investment: Evidence from a hazard model. Journal of Financial Economics 102, 643–670.

Cornaggia, J., Wolfe, B., Yoo, W., 2018. Crowding out Banks: Credit Substitution by Peer-To-Peer Lending, unpublished working paper, Pennsylvania State University.

Goldstein, M.A., Irvine, P., Puckett, A., 2011. Purchasing IPOs with commissions. Journal of Financial and Quantitative Analysis 46, 1193–1225.

Havrylchyk, O., Mariotto, C., Rahim, T., Verdier, M., 2016. What drives the expansion of the peer-to-peer lending?, unpublished working paper. LEM, University of Lille.

Heckman, J., 1979. Sample Specification Bias as a Selection Error. Econometrica 47, 153–162.

Hornuf, L., Schmitt, M., 2016. Does a local bias exist in equity crowdfunding? The impact of investor types and portal design, unpublished working paper. University of Trier, No. 16-07.

Jackson, R.J., Squire, R., Honigsberg, C., 2016. What Happens when Loans Become Legally Void ? Evidence from a Natural Experiment, unpublished working paper. Stanford.

Kostovetsky, L., Benedetti, H., 2018. Digital Tulips? Returns to Investors in Initial Coin Offerings, SSRN Electronic Journal, unpublished working paper.

Lin, M., Prabhala, N.R., Viswanathan, S., 2013. Judging Borrowers by the Company They Keep: Friendship Networks and Information Asymmetry in Online Peer-to-Peer Lending. Management Science 59, 17–35.

Lin, M., Sias, R., Wei, Z., 2015. “Smart Money”: Institutional Investors in Online Crowdfunding, unpublished working paper. University of Arizona.

Lin, M., Viswanathan, S., 2015. Home Bias in Online Investments: An Empirical Study of an Online Crowd Funding Market. Management Science.

Loughran, T., Ritter, J., 2004. Why has IPO underpricing changed over time? Financial management 5–37.

Loughran, T., Ritter, J.R., 2002. Why Don't Issuers Get Upset About Leaving Money on the Table in IPOs? Review of Financial Studies 15, 413–443.

Lowry, M., Michaely, R., Volkova, E., 2017. Initial Public Offerings: A synthesis of the literature and directions for future research, unpublished working paper LeBow College of Business, Drexel University.

Meyer, B.D., 1990. Unemployment Insurance and Unemployment Spells. Econometrica 58, 757–782.

Mohammadi, A., Shafi, K., 2017. How wise are crowd? A comparative study of crowd and institutions. Academy of Management Proceedings.

Rajan, U., Seru, A., Vig, V., 2015. The failure of models that predict failure: Distance, incentives, and defaults. Journal of Financial Economics 115, 237–260.

Rajan, U., Seru, A., Vig, V., 2010. Statistical default models and incentives. American Economic Review 100, 506–510.

Ravina, E., 2018. Love & Loans The Effect of Beauty and Personal Characteristics in, unpublished working paper Northwestern University.

Reuter, J., 2006. Are IPO Allocations for Sale ? Evidence from Mutual Funds. Journal of Finance LXI, 2289–2324.

Ritter, J.R., Zhang, D., 2007. Affiliated mutual funds and the allocation of initial public offerings. Journal of Financial Economics 86, 337–368.

Roberts, M.R., Whited, T.M., 2011. Endogeneity in Empirical Corporate Finance Endogeneity in Empirical Corporate Finance. SSRN Electronic Journal 1–97.

Rock, K., 1986. Why new issues are underpriced. Journal of Financial Economics 15, 187–212.

Senney, G.T., 2016. The Geography of Bidder Behavior in Peer-to-Peer Lending Markets, unpublished working paper, The Ohio State University.

Sherman, A.E., 2000. IPOs and long-term relationships: An advantage of book building. Review of Financial Studies 13, 697–714.

Sherman, A.E., Titman, S., 2002. Building the IPO order book: Underpricing and participation limits with costly information. Journal of Financial Economics 65, 3–29.

Tang, H., 2018. Peer-to-Peer Lenders versus Banks : Substitutes or Complements ? How does it work? forthcoming Review of Financial Studies.

Vallee, B., Zeng, Y., 2018. Marketplace Lending: A New Banking Paradigm? forthcoming Review of Financial Studies.

Venkatesan, S., Wolfe, B., Yoo, W., 2018. The Nexus of Marketability , Market Segmentation , and Platform Pricing Mechanisms in Peer-to-peer Lending, unpublished working paper, Western Ontario University.

Welch, I., 1989. Seasoned offerings, imitation costs, and the underpricing of initial public offerings. The Journal of Finance 44, 421–449.

Zhang, J., Liu, P., 2012. Rational Herding in Microloan Markets. Management Science 58, 892–912.

Appendix: Variable Definitions

Variable	Definition
$Default_{it}$	An indicator equal to one when a loan is defaulted, charged off, or is delinquent by more than 30 days.
$Prepayment_{it}$	An indicator equal to one when a loan is fully paid before the maturity date.
$Whole_{it}$	An indicator equal to one when a loan is initially assigned to the whole loan market

Borrower Credit Information

DTI_{it}	The borrower's debt to income ratio (%).
$Inq6Month_{it}$	Number of credit inquiries on borrower's credit report in the six months before listing.
$YrsFirstCredit_{it}$	Borrower's credit history length, i.e. the number of years between borrower's first credit line and the time of listing.
$Utilization_{it}$	The percentage of credit lines that the borrower has used at the time of listing. Note, the quadratic term is multiplied by 0.01 in order to have the appropriate scale of coefficient.
$EmployLen_{it}$	Borrower's employment length in years. Possible values are the integer values from 0 to 10. Employment length less than one year is 0, Ten or more years of employment length is 10.
$RiskScore_{it}$	Borrower's FICO score category. The score category ranges from 1 to 12 . e.g., Category 1 means FICO scores between 636 and 654 (the lowest FICO group). Category 12 means FICO scores between 835 and 850 (the highest FICO group).

Loan information

$Amount_{it}$	The log of the loan amount in US dollars requested by the borrower.
$5YearTerm_{it}$	An indicator equal to one if the loan term is equal to five years and equal to zero if it is a three year term loan.
$IntRate_{it}$	LendingClub: the stated interest rate, the rate the investor should receive on their investment, which is approximate to the coupon rate minus any service charge. Prosper: the lender yield, which is the coupon minus service fee.
$CreditGrade_{it}$	Credit grade of a loan assigned by the platform: LendingClub (A, B, C, D, E, F, G), Prosper (AA, A, B, C, D, E, HR).

$Purpose_{it}$	A series of dummy variable indicating purpose of borrowing. For LendingClub these include: debt consolidation, credit card, home improvement, medical/moving/vacation/wedding/major purchase, small business, education, car, others. For Prosper these include: not available, debt consolidation, home improvement, business, personal loan, student use, auto, other, baby & adoption, boat, cosmetic procedure, engagement ring, green loans, household expenses, large purchases, medical/dental, motorcycle, rv, taxes, vacation, wedding loans.
W/W_{it}	An indicator equal to one when a loan is initially assigned to the whole loan market and funded in the whole loan market
W/F_{it}	An indicator equal to one when a loan is initially assigned to the whole loan market but funded in the fractional market

Platform Characteristics

$Rollover_t$	The fraction of the dollar volume of loans that, after remaining unfunded in the whole loan market, are rolled over to the fraction market relative to the total dollar volume of loans initially allocated to the whole loan market in week t.
$HighRollover_t$	An indicator equal to one if Rollover is larger than its median.
$Quiet_t$	An indicator equal to one during the period 2016Q2 till 2017Q1 when no securitization activity occurs on the Prosper Platform.
$FracPercent_t$	The fraction of the dollar volume of loans that pass Prosper's credit screen and are assigned to the fractional market relative to the total dollar volume of loans that pass the credit screen and are placed for funding in both the active funding markets in week t within the same credit grade
$HighFreedom_t$	An indicator equal to one if FracPercent is larger than its first quartile within the same credit grade.

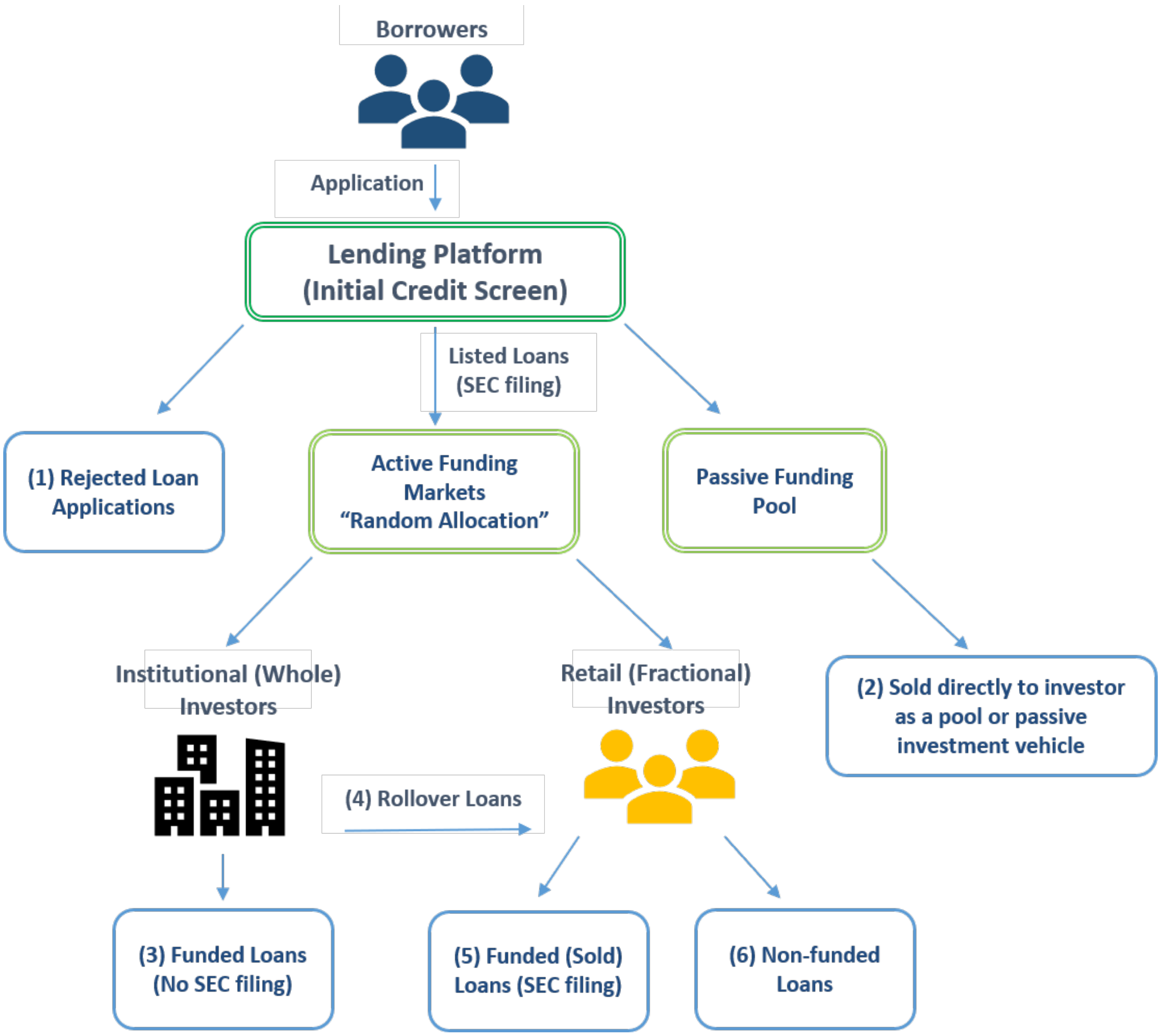


Figure 1 – Loan Allocation process

In this figure, we show the standard loan allocation process. After borrowers submit a loan application, the platform performs a credit screen (1) rejecting the majority of loan applications. After passing the initial screen, loans are allocated to one of three funding markets: Passive funding pool, Active Funding Market (Retail), or Active Funding Market (Institutional). Loans allocated to the passive pool (2) are packaged in groups and sold to institutional investors or used to back passive investment funds offered to investors. In the active funding markets, investors compete to fund the loans. Loans funded in the active institutional funding market (3) are not registered with the SEC. Loans not funded in the active institutional market roll over to be funded (4) in the retail market. Retail market loans that are funded are registered as sold loans (5) with the SEC. Loans not funded in the retail market are either funded by the platform (6) or remain unfunded.

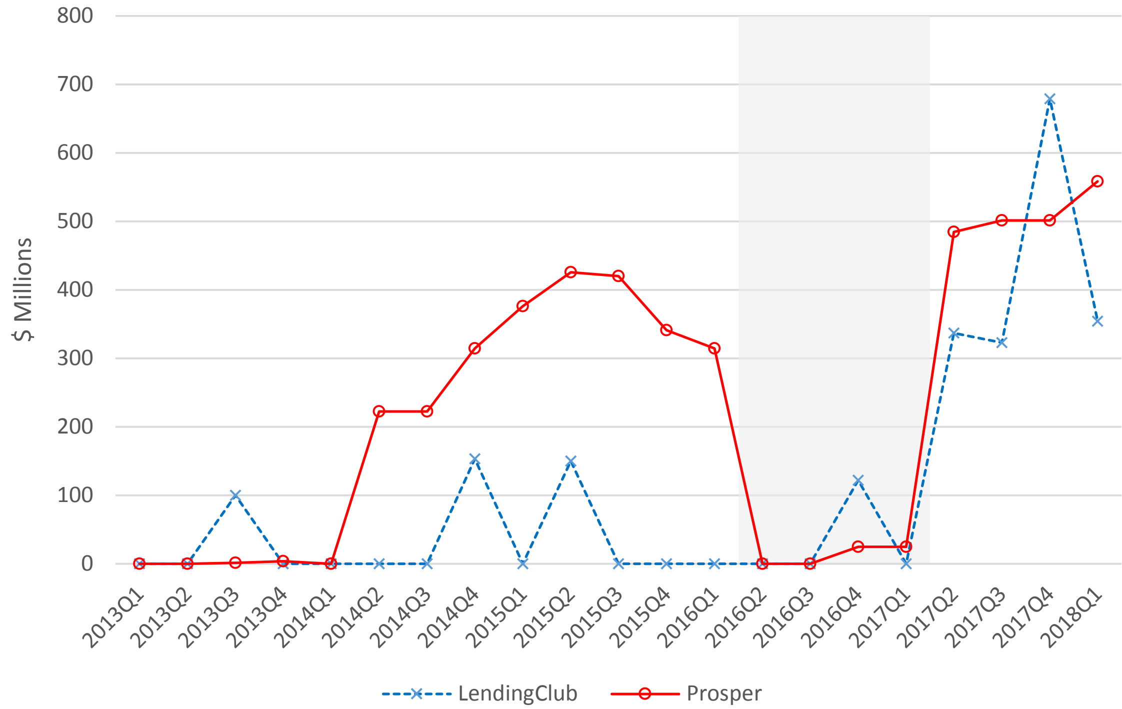


Figure 2: Quarterly Securitization Volume per Marketplace Lending Platform

This figure reports volume of loans funded (purchased) each quarter by asset backed security (ABS) issuers on the marketplace lending platform. Marketplace lending platforms allow ABS issuers to fund a predetermined amount of loans that the ABS issuer will pool and use to create ABSs to sell to their clients. The total loan funding activity (million dollars) across all ABS issuers within a quarter is reported. The shaded quarters represent the period when funding activity for ABS securities on Prosper was dramatically reduced prior to the enforcement of credit retention rules from the JOBS Act and corresponds to our *Quiet* dummy used later. ABS securitization after the shaded period is performed almost exclusively by marketplace lending platforms while prior to that period ABSs were issued almost entirely by financial firms outside the marketplace lending platform.

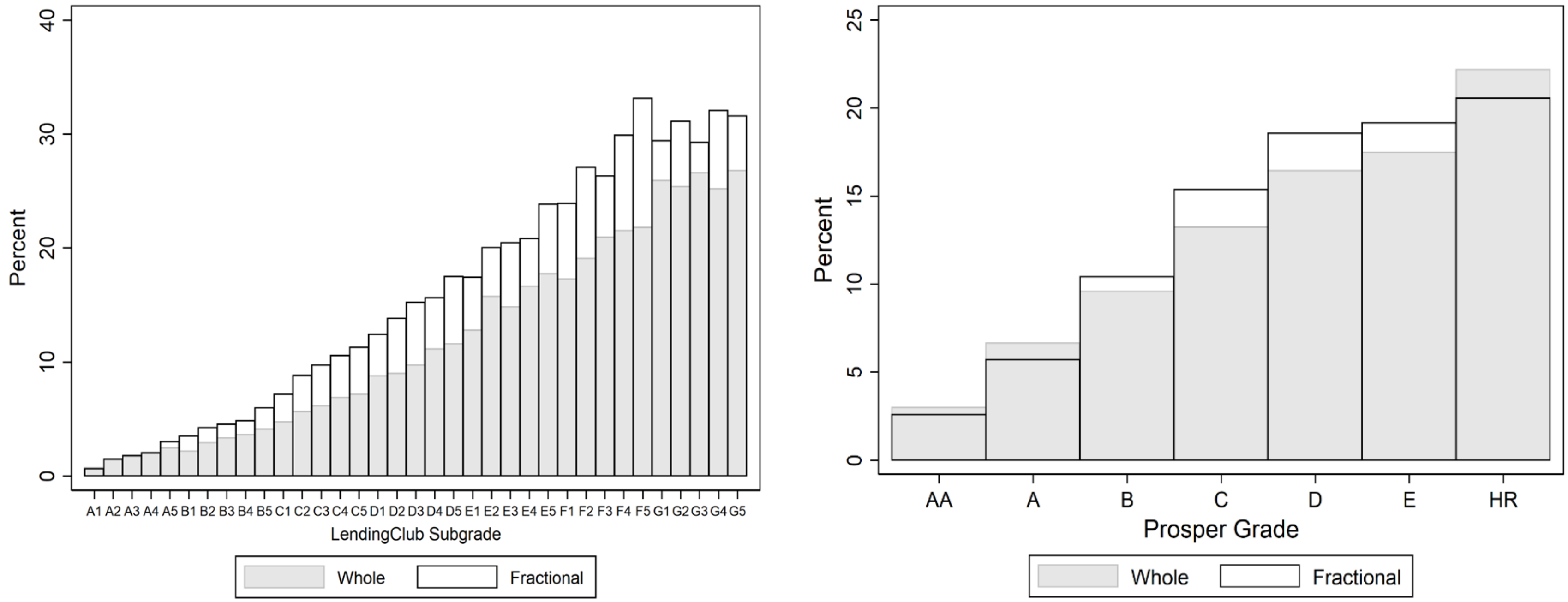


Figure 3: Default Rate for each Marketplace Lending Platform by Funding Market and Credit Grade

This figure shows the average default rate over our sample period for each marketplace lending platform by credit grade and active funding market. The whole loan market is primarily institutional investors that fund a loan in its entirety while the fractional market is composed of retail investors funding a portion of each borrower's loan. A loan is considered in default if it is more than 30 days delinquent.

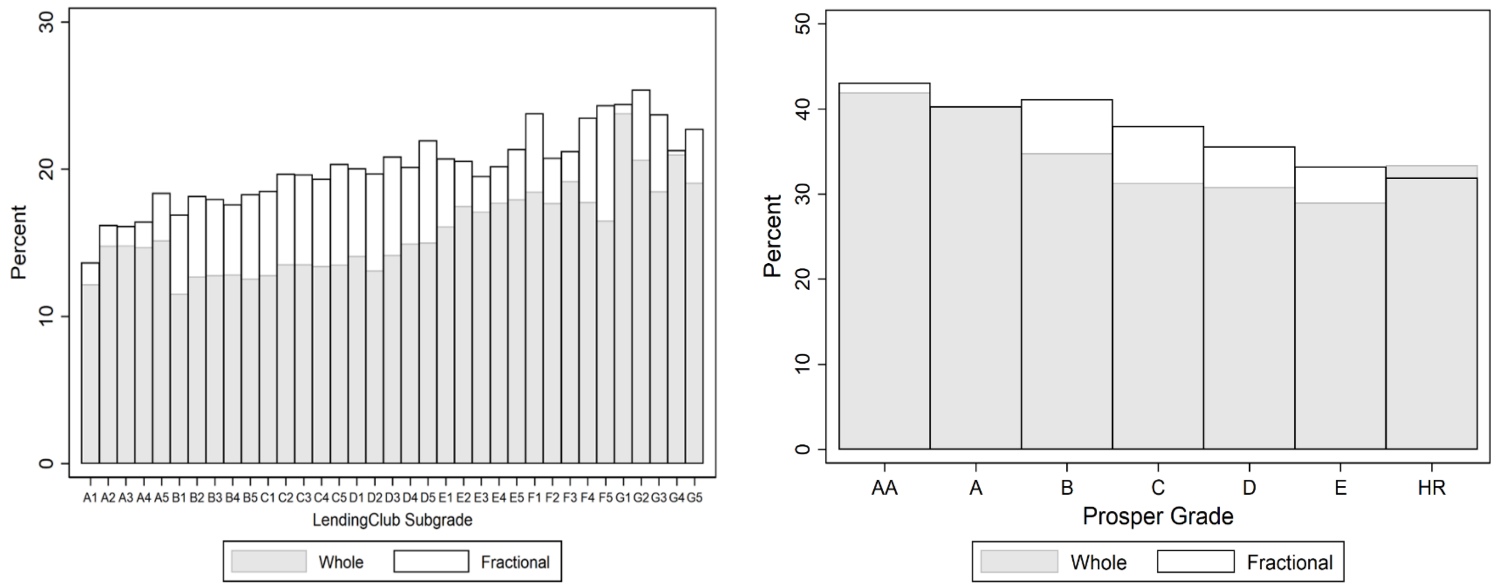
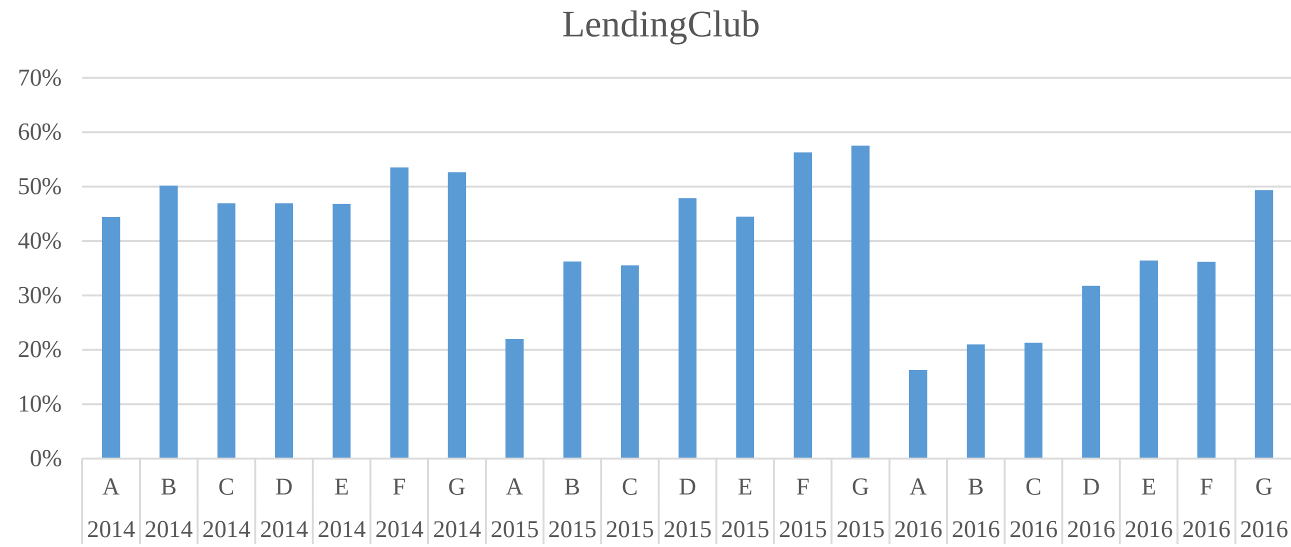


Figure 4: Prepayment Rate for each Marketplace Lending Platform by Funding Market and Credit Grade

This figure shows the average prepayment rate over our sample period for each marketplace lending platform by credit grade and active funding market. The whole loan market is primarily institutional investors that fund a loan in its entirety while the fractional market is composed of retail investors funding a portion of each borrower's loan.



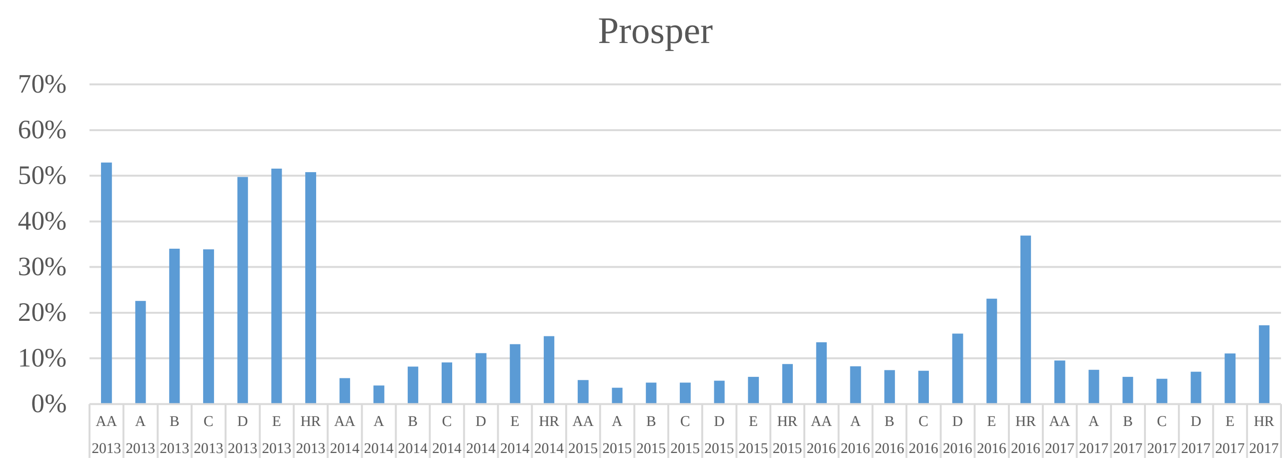


Figure 5. Annual Dollar Fraction of Loans Allocated to the Fractional (Retail) Market by Loan Credit Rating.

As loan applications pass a platform credit screen, loans are allocated to either the whole (institutional) loan active funding market or the fractional (retail) active funding market. This figure reports the dollar portion of loans assigned to the fractional loan market by credit rating each year for LendingClub (top) and Prosper (bottom).

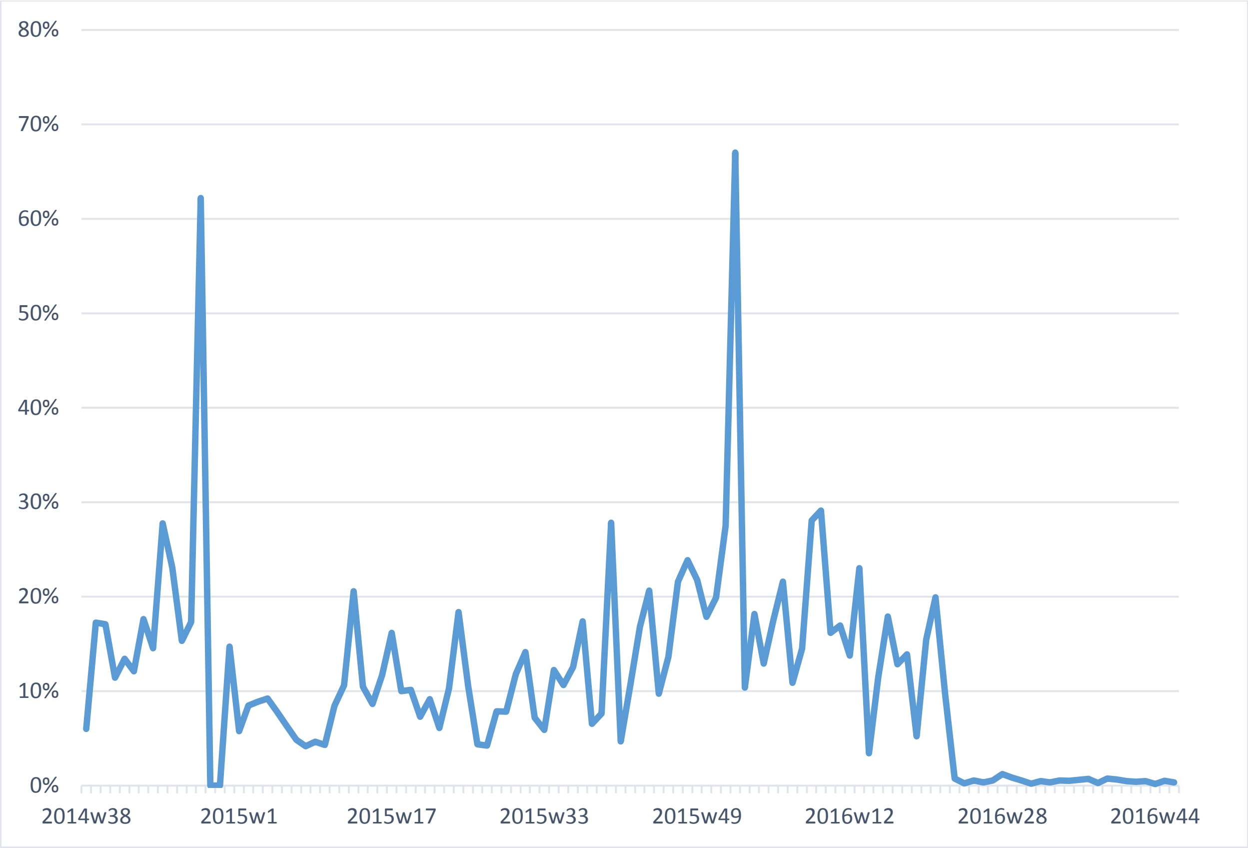


Figure 6. Weekly Rollover Ratio of Whole (Institutional) Loans on LendingClub

After loans are allocated to the whole loan active funding (institutional) market, if they are unfunded after a certain period of time, usually 1-12 hours, the platform rolls them over to the fractional active funding market for retail investors to fund. This figure reports the weekly dollar fraction of loans initially assigned to the whole loan market that are rolled over to fractional market relative to the total loan volume (in dollars) initially assigned to the whole loan market.

Table 1. Summary Statistics by Platform and Initial Market Assignment

Summary statistics of our main variables are presented below for each marketplace lending platform and separated by funding market. Panel A presents statistics for the marketplace lending platform LendingClub and Panel B for Prosper. After a loan application is received by the platform, it is initially assigned to either the retail (Fractional) funding market or the institutional (Whole) funding market.

Panel A. LendingClub

	Fractional (F)			Whole (W)				
Variable	N	Mean	Std. Dev.	N	Mean	Std. Dev.	Diff.	t-stat
$Inq6Month_{it}$	271,398	0.639	0.921	636,554	0.539	0.838	0.101***	50.835
$YrsFirstCredit_{it}$	271,398	16.254	7.590	636,554	16.942	7.674	-0.688***	-39.241
$Utilization_{it}$	271,398	53.867	23.947	636,554	51.924	24.095	1.943***	35.247
$EmployLen_{it}$	271,398	5.599	3.816	636,554	5.779	3.815	-0.180***	-20.597
$Amount_{it}$	271,398	9.339	0.704	636,554	9.447	0.670	-0.108***	-69.285
$5YearTerm_{it}$	271,398	0.197	0.398	636,554	0.339	0.473	-0.141***	-140.000
$IntRate_{it}$	271,398	13.653	4.701	636,554	12.467	4.505	1.186***	113.384
$RiskScore_{it}$	271,398	3.558	1.631	636,554	3.892	1.797	-0.334***	-83.204

Panel B. Prosper

	Fractional (F)			Whole (W)				
Variable	N	Mean	Std. Dev.	N	Mean	Std. Dev.	Diff.	t-stat
$Inq6Month_{it}$	29,661	0.974	1.315	258,614	1.028	1.336	-0.054***	-6.615
$YrsFirstCredit_{it}$	29,661	18.475	8.289	258,614	18.406	8.416	0.069	1.333
$Utilization_{it}$	29,661	55.622	27.598	258,614	53.658	26.569	1.963***	12.006
$EmployLen_{it}$	29,661	5.911	3.832	258,614	5.870	3.858	0.041*	1.741
$Amount_{it}$	29,661	9.119	0.698	258,614	9.233	0.711	-0.114***	-26.234
$5YearTerm_{it}$	29,661	0.372	0.483	258,614	0.346	0.476	0.026***	8.967
$IntRate_{it}$	29,661	15.879	6.723	258,614	13.698	5.630	2.181***	61.850

Table 2. Summary Statistics by Platform and Initial Market Assignment/Credit Grade

This table reports the sample mean of our main variables for each marketplace lending platform grouped by market assignment and credit grade. Panel A presents statistics for the marketplace lending platform LendingClub and Panel B for Prosper. After a loan application is received by the platform, the platform assigns a credit grade to the loan ranging from A (safest) to G (riskiest) on LendingClub or AA (safest) to HR, high risk (riskiest) on Prosper. Then it is initially assigned to either the retail (Fractional) funding market or the institutional (Whole) funding market.

Panel A. LendingClub

	Fractional (F)							Whole (W)						
Variable	A	B	C	D	E	F	G	A	B	C	D	E	F	G
$Inq6Month_{it}$	0.309	0.471	0.667	0.820	0.907	1.033	1.184	0.308	0.454	0.602	0.727	0.821	0.980	1.108
$YrsFirstCredit_{it}$	18.567	17.003	15.752	15.390	15.128	14.713	14.162	18.758	17.283	16.316	15.817	15.624	15.129	14.374
$Utilization_{it}$	42.452	52.336	56.108	57.299	57.802	57.039	56.144	41.093	51.200	55.523	57.483	58.489	57.993	56.755
$EmployLen_{it}$	5.842	5.698	5.507	5.465	5.517	5.660	5.608	5.892	5.780	5.726	5.711	5.818	5.783	5.607
$Amount_{it}$	9.393	9.287	9.250	9.344	9.516	9.682	9.731	9.414	9.358	9.428	9.549	9.744	9.801	9.811
$5YearTerm_{it}$	0.026	0.099	0.145	0.257	0.488	0.714	0.794	0.056	0.224	0.405	0.556	0.819	0.883	0.887
$IntRate_{it}$	7.045	10.221	13.486	17.120	20.327	24.301	27.545	6.925	10.171	13.600	17.528	20.605	24.781	27.817
$RiskScore_{it}$	5.225	3.714	3.264	3.101	3.049	3.026	2.942	5.356	3.890	3.440	3.231	3.151	3.050	2.941
N	32,061	75,300	75,279	51,079	26,033	9,157	2,489	123,274	188,630	192,221	79,405	39,261	11,296	2,467

Panel B. Prosper

	Fractional (F)							Whole (W)						
Variable	AA	A	B	C	D	E	HR	AA	A	B	C	D	E	HR
$Inq6Month_{it}$	0.450	0.687	0.877	1.084	1.195	1.336	1.192	0.493	0.740	0.963	1.201	1.381	1.442	1.594
$YrsFirstCredit_{it}$	20.509	19.318	18.838	18.188	17.639	17.201	17.254	20.231	19.141	18.605	17.984	17.426	16.696	16.413
$Utilization_{it}$	31.924	45.203	54.298	60.046	63.354	66.122	69.502	34.159	46.981	53.211	58.088	62.718	65.793	67.477
$EmployLen_{it}$	6.150	5.998	5.990	5.897	5.854	5.664	5.529	6.114	5.989	5.936	5.819	5.708	5.499	5.340
$Amount_{it}$	9.187	9.257	9.283	9.197	9.051	8.719	8.333	9.175	9.287	9.339	9.294	9.160	8.744	8.310
$5YearTerm_{it}$	0.067	0.266	0.419	0.463	0.486	0.411	0.000	0.031	0.201	0.388	0.467	0.469	0.393	0.000
$IntRate_{it}$	5.960	8.876	12.376	16.402	21.484	26.384	29.937	5.807	8.632	11.608	15.590	20.586	25.558	29.170
N	2,878	4,009	6,159	7,528	5,055	3,028	1,004	22,842	53,201	60,924	72,175	31,615	14,812	3,045

Table 3. Default and Prepayment for LendingClub loans based on Initial Assignment

This table reports hazard ratios, i.e. the exponential form of the coefficients, for two types of loan termination, default and prepayment, for loans originated on LendingClub during the period 9/21/2014 - 12/31/2016. Hazard ratios greater than one suggest the variables have a positive association with default while ratios less than one have a negative association with default. We estimate a Cox proportional hazard model for default in columns (1) – (3) and prepayment in columns (4) – (6). Columns (1) and (4) model the full sample of loans. We then split the sample by credit grade and report hazard ratios for investment grade (IG) loans in columns (2) and (5) and riskier high yield (HY) loans in columns (3) and (6). All the models contain indicators for credit grade, debt-to-income (DTI) quartile, and loan purpose. The models also contain quarter-year fixed effects. The chi-square statistics are reported in parentheses. "***", "**", and "*" denote statistical significance at the 1%, 5%, and 10% level respectively.

	$Default_{it}$			$Prepayment_{it}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$Whole_{it}$	0.969***	0.985	0.951***	0.987**	0.983**	0.992
	(10.08)	(1.04)	(13.53)	(4.07)	(5.03)	(0.42)
$Inq6Month_{it}$	1.105***	1.119***	1.096***	1.045***	1.042***	1.053***
	(465.37)	(227.93)	(238.1)	(183.03)	(97.19)	(95.65)
$YrsFirstCredit_{it}$	0.99***	0.994***	0.987***	0.997***	0.996***	1.001*
	(188.75)	(45.85)	(165.13)	(45.17)	(75.15)	(2.74)
$Utilization_{it}$	0.988***	0.987***	0.988***	0.98***	0.978***	0.986***
	(243.90)	(128.06)	(118.47)	(1997.0)	(1754.4)	(233.84)
$Utilization_{it}^2$	1.008***	1.009***	1.007***	1.011***	1.012***	1.006***
	(123.89)	(78.00)	(48.43)	(652.66)	(578.99)	(58.09)
$Amount_{it}$	1.132***	1.075***	1.206***	0.984***	0.961***	1.064***
	(232.63)	(43.04)	(243.23)	(11.05)	(52.00)	(39.86)
$IntRate_{it}$	1.36***	1.55***	1.197***	1.09***	1.14***	1.063**
	(442.22)	(140.61)	(25.13)	(133.51)	(79.80)	(4.46)
$IntRate_{it}^2$	0.995***	0.99***	0.998**	0.999**	0.997***	1.000
	(141.16)	(45.20)	(4.63)	(6.17)	(17.12)	(0.27)
$5YearTerm_{it}$	0.671***	0.635***	0.697***	0.638***	0.607***	0.671***
	(1126.1)	(650.64)	(489.12)	(3023.1)	(2374.9)	(779.55)
$EmployLen_{it}$	0.985***	0.983***	0.986***	1.009***	1.009***	1.007***
	(144.38)	(91.17)	(60.40)	(123.34)	(99.21)	(19.59)
$CreditGrade_{it}$	All	IG	HY	All	IG	HY
DTI $Level_{it}$	Yes	Yes	Yes	Yes	Yes	Yes
Loan $Purpose_{it}$	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effect	Year-Qtr	Year-Qtr	Year-Qtr	Year-Qtr	Year-Qtr	Year-Qtr
Observation	714,906	545,844	169,062	787,948	611,960	175,988

Table 4. Default and Prepayment for Prosper loans based on Initial Assignment

This table reports hazard ratios for two types of loan termination, default and prepayment, for loans originated on Prosper during the period 3/25/2013 - 12/31/2017. Hazard ratios greater than one suggest the variables have a positive association with default while ratios less than one have a negative association with default. We estimate a Cox proportional hazard model for default in columns (1) – (3) and prepayment in columns (4) – (6). Columns (1) and (4) model the full sample of loans. We then split the sample by credit grade and report hazard ratios for investment grade (IG) loans in columns (2) and (5) and riskier high yield (HY) loans in columns (3) and (6). All the models contain indicators for credit grade, debt-to-income (DTI) quartile, and loan purpose. The models also contain quarter-year fixed effects. The chi-square statistics are reported in parentheses. "***", "**", and "*" denote statistical significance at the 1%, 5%, and 10% level respectively.

	$Default_{it}$			$Prepayment_{it}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$Whole_{it}$	1.025	1.071**	1.010	1.009	0.998	1.023
	(2.21)	(4.27)	(0.25)	(0.89)	(0.02)	(2.57)
$Inq6Month_{it}$	1.094***	1.121***	1.085***	1.087***	1.097***	1.076***
	(673.47)	(270.47)	(403.89)	(1521.8)	(845.62)	(631.50)
$YrsFirstCredit_{it}$	0.99***	0.989***	0.99***	0.994***	0.993***	0.995***
	(284.34)	(110.43)	(162.02)	(303.5)	(214.58)	(92.82)
$Utilization_{it}$	0.995***	0.994***	0.996***	0.989***	0.988***	0.992***
	(35.33)	(21.70)	(14.64)	(634.89)	(472.96)	(133.82)
$Utilization_{it}^2$	1.002**	1.003***	1.001	1.007***	1.008***	1.004***
	(5.51)	(7.44)	(0.63)	(281.27)	(201.02)	(51.37)
$Amount_{it}$	1.125***	0.977*	1.219***	1.021***	0.996	1.064***
	(207.26)	(2.91)	(362.56)	(20.78)	(0.43)	(73.92)
$IntRate_{it}$	1.18***	1.303***	1.124***	1.014**	0.975*	1.051***
	(185.00)	(44.85)	(40.51)	(5.02)	(2.95)	(15.03)
$IntRate_{it}^2$	0.998***	0.993***	0.999	1.001***	1.003***	1.000
	(28.79)	(13.73)	(2.59)	(11.10)	(15.63)	(1.45)
$5YearTerm_{it}$	0.703***	0.685***	0.712***	0.532***	0.498***	0.562***
	(1000.)	(319.78)	(659.06)	(7750.9)	(4191.5)	(3492.2)
$EmployLen_{it}$	0.987***	0.988***	0.987***	1.001	1.000	1.003**
	(93.01)	(28.66)	(63.32)	(1.49)	(0.17)	(5.24)
$CreditGrade_{it}$	All	IG	HY	All	IG	HY
DTI $Level_{it}$	Yes	Yes	Yes	Yes	Yes	Yes
Loan $Purpose_{it}$	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effect	Year-Qtr	Year-Qtr	Year-Qtr	Year-Qtr	Year-Qtr	Year-Qtr
Observation	169,143	82,781	86,362	249,356	137,190	112,166

Table 5. Default and Prepayment for LendingClub loans based on Initial Assignment Before and After Management Reorganization

This table reports hazard ratios for two types of loan termination, default in Panel A and prepayment in Panel B, for loans originated on LendingClub during the period 9/21/2014 - 12/31/2016. Hazard ratios greater than one suggest the variables have a positive association with default while ratios less than one have a negative association with default. We estimate a Cox proportional hazard model for the sample before the management reorganization in columns (1) – (3) and after reorganization in columns (4) – (6). Columns (1) and (4) model the full subsample of loans. We then further divide the subsample by credit grade and report hazard ratios for investment grade (IG) loans in columns (2) and (5) and riskier high yield (HY) loans in columns (3) and (6). All the models contain indicators for credit grade, debt-to-income (DTI) quartile, and loan purpose. The models also contain quarter-year fixed effects. The chi-square statistics are reported in parentheses. "***", "**", and "*" denote statistical significance at the 1%, 5%, and 10% level respectively.

Panel A – Default

	Before May 2016			After May 2016		
	(1)	(2)	(3)	(4)	(5)	(6)
$Whole_{it}$	0.974***	0.988	0.957***	0.81***	0.937	0.712***
	(6.72)	(0.66)	(9.59)	(16.24)	(0.73)	(21.59)
$Inq6Month_{it}$	1.104***	1.118***	1.095***	1.124***	1.157***	1.1***
	(429.22)	(211.1)	(218.92)	(25.16)	(17.16)	(9.38)
$YrsFirstCredit_{it}$	0.99***	0.993***	0.987***	1.001	1.008*	0.991*
	(197.49)	(55.0)	(158.93)	(0.04)	(3.40)	(2.84)
$Utilization_{it}$	0.988***	0.988***	0.988***	0.983***	0.982***	0.984***
	(223.83)	(115.23)	(110.51)	(22.03)	(13.26)	(9.63)
$Utilization_{it}^2$	1.008***	1.009***	1.007***	1.013***	1.016***	1.012**
	(112.30)	(68.90)	(45.02)	(15.24)	(10.95)	(5.43)
$Amount_{it}$	1.123***	1.072***	1.188***	1.251***	1.106**	1.468***
	(189.00)	(37.04)	(192.46)	(34.39)	(3.96)	(42.71)
$IntRate_{it}$	1.356***	1.541***	1.206***	1.378***	1.48**	1.043
	(368.20)	(126.97)	(21.35)	(19.13)	(4.78)	(0.06)
$IntRate_{it}^2$	0.995***	0.99***	0.998*	0.994***	0.992	1.001
	(101.44)	(39.73)	(3.54)	(8.95)	(1.30)	(0.01)
$5YearTerm_{it}$	0.677***	0.639***	0.705***	0.562***	0.533***	0.586***
	(1013.8)	(598.5)	(428.8)	(87.68)	(43.10)	(42.57)
$EmployLen_{it}$	0.986***	0.983***	0.987***	0.976***	0.982**	0.969***
	(125.39)	(82.75)	(49.67)	(14.15)	(4.48)	(10.98)
$CreditGrade_{it}$	All	IG	HY	All	IG	HY
DTI $Level_{it}$	Yes	Yes	Yes	Yes	Yes	Yes
Loan $Purpose_{it}$	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effect	Year-Qtr	Year-Qtr	Year-Qtr	Year-Qtr	Year-Qtr	Year-Qtr
Observation	503,715	378,734	124,981	187,709	148,488	39,221

Panel B – Prepayment

	Before May 2016			After May 2016		
	(1)	(2)	(3)	(4)	(5)	(6)
$Whole_{it}$	0.993	0.989	1.002	0.918***	0.935**	0.863***
	(1.03)	(1.88)	(0.03)	(12.92)	(5.45)	(11.34)
$Inq6Month_{it}$	1.049***	1.044***	1.059***	1.015	1.024	1.005
	(192.27)	(96.21)	(105.38)	(1.67)	(2.63)	(0.05)
$YrsFirstCredit_{it}$	0.997***	0.995***	1.001	1.001	1.001	1.004
	(54.70)	(84.15)	(1.42)	(0.74)	(0.12)	(1.46)
$Utilization_{it}$	0.98***	0.979***	0.986***	0.976***	0.975***	0.98***
	(1673.1)	(1465.)	(190.92)	(255.90)	(203.73)	(47.07)
$Utilization_{it}^2$	1.011***	1.012***	1.006***	1.015***	1.015***	1.011***
	(534.76)	(470.93)	(46.30)	(89.09)	(68.2)	(15.44)
$Amount_{it}$	0.988**	0.965***	1.064***	0.966**	0.932***	1.093***
	(5.92)	(35.96)	(35.35)	(4.60)	(14.36)	(7.12)
$IntRate_{it}$	1.119***	1.147***	1.12***	1.059**	1.15***	1.022
	(162.88)	(76.44)	(8.96)	(4.86)	(7.98)	(0.05)
$IntRate_{it}^2$	0.998***	0.997***	0.998**	1.001	0.997	1.001
	(34.85)	(19.19)	(4.37)	(0.58)	(2.14)	(0.38)
$5YearTerm_{it}$	0.624***	0.594***	0.657***	0.796***	0.759***	0.826***
	(3001.2)	(2349.8)	(774.75)	(62.25)	(55.54)	(15.73)
$EmployLen_{it}$	1.008***	1.008***	1.005***	1.021***	1.02***	1.022***
	(82.18)	(70.21)	(10.08)	(52.15)	(32.98)	(16.11)
$CreditGrade_{it}$	All	IG	HY	All	IG	HY
DTI $Level_{it}$	Yes	Yes	Yes	Yes	Yes	Yes
Loan $Purpose_{it}$	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effect	Year-Qtr	Year-Qtr	Year-Qtr	Year-Qtr	Year-Qtr	Year-Qtr
Observation	567,817	437,765	130,052	195,377	154,429	40,948

Table 6. Simultaneous Estimation of Prepayment and Default exit for LendingClub

This table reports *coefficients* for the simultaneous estimation of default and prepayment using loans originated on LendingClub during the period 9/21/2014 - 12/31/2016. We assume a Gamma baseline hazard within a frailty model and use maximum likelihood to estimate the determinants of the joint exit events, default and prepayment, for the sample before the 2016 Q2 management reorganization in columns (1) – (2) and after reorganization in columns (3) – (4). We convert loan credit grade to an ordinal ranking of credit grades (Credit Grade) and use the cardinal year of issue (Issue YO) to aid in convergence of the estimation. Standard errors are reported in parentheses. "***", "**", and "*" denote statistical significance at the 1%, 5%, and 10% level respectively. Gamma is the inverse scale parameter estimate while LogSig is the estimate of the random effect's variance (log standard deviation of the distribution).

	Before May 2016			After May 2016		
	Single Model	Simultaneous Model		Single Model	Simultaneous Model	
	$Default_{it}$	$Default_{it}$	$Prepayment_{it}$	$Default_{it}$	$Default_{it}$	$Prepayment_{it}$
$Whole_{it}$	-0.067***	-0.052***	-0.037***	-0.077***	-0.066***	-0.054***
	(0.007)	(0.051)	(0.005)	(0.024)	(0.021)	(0.016)
DTI $Quartile_{it}$	0.048***	0.021***	-0.089***	-0.008	-0.008	-0.086***
	(0.003)	(0.002)	(0.002)	(0.011)	(0.009)	(0.007)
$Amount_{it}$	-0.019***	0.009**	0.046***	-0.059***	-0.061***	0.062***
	(0.006)	(0.004)	(0.003)	(0.017)	(0.015)	(0.011)
$5YearTerm_{it}$	-0.237***	-0.215***	-0.291***	-0.277***	-0.26***	-0.068***
	(0.008)	(0.006)	(0.006)	(0.03)	(0.027)	(0.02)
Issued YQ_{it}	0.084***	0.083***	0.062***	-0.026	0.001	0.251***
	(0.002)	(0.001)	(0.001)	(0.021)	(0.02)	(0.013)
Credit $Grade_{it}$	0.364***	0.297***	0.132***	0.274***	0.246***	0.122***
	(0.003)	(0.002)	(0.002)	(0.011)	(0.01)	(0.007)
Intercept	6.596***	6.200***	6.592***	7.294***	6.696***	5.683***
	(0.052)	(0.039)	(0.035)	(0.178)	(0.162)	(0.111)
Gamma	3.032***	2.541***	1.761***	4.448***	2.476***	1.53***
	(0.061)	(0.039)	(0.014)	(0.418)	(0.059)	(0.016)
LogSig	0.124***	-0.169***		0.038	-1.364***	
	(0.007)	(0.011)		(0.025)	(0.454)	
Observations	675,018	675,018		198,509	198,509	
Log Likelihood	-905,656	-2,940,000		-33,395	-189,532	

Table 7. Simultaneous Estimation of Prepayment and Default exit for Prosper

This table reports *coefficients* for the simultaneous estimation of default and prepayment using loans originated on Prosper during the period 3/25/2013 - 12/31/2017. We assume a Gamma baseline hazard within a frailty model and use maximum likelihood to estimate the determinants of the joint exit events, default and prepayment, for each year of the sample. We convert loan credit grade to an ordinal ranking of credit grades (Credit Grade) and use the cardinal year of issue (Issue YQ) to aid in convergence of the estimation. Standard errors are reported in parentheses. "***", "**", and "*" denote statistical significance at the 1%, 5%, and 10% level respectively. Gamma is the inverse scale parameter estimate while LogSig is the estimate of the random effect's variance (log standard deviation of the distribution).

	Model 1: Year 2013		Model 2: Year 2014		Model 3: Year 2015		Model 4: Year 2016		Model 5: Year 2017	
	$Default_{it}$	$Prepayment_{it}$	$Default_{it}$	$Prepayment_{it}$	$Default_{it}$	$Prepayment_{it}$	$Default_{it}$	$Prepayment_{it}$	$Default_{it}$	$Prepayment_{it}$
$Whole_{it}$	0.025	-0.006	0.012	0.010	0.032	0.028*	-0.005	-0.029*	0.022	0.005
	(0.023)	(0.012)	(0.022)	(0.012)	(0.029)	(0.016)	(0.027)	(0.017)	(0.057)	(0.029)
DTI $Quartile_{it}$	0.082***	-0.057***	0.072***	-0.063***	0.112***	-0.045***	0.102***	-0.054***	-0.002	-0.071***
	(0.012)	(0.006)	(0.007)	(0.003)	(0.008)	(0.004)	(0.011)	(0.006)	(0.018)	(0.008)
$Amount_{it}$	-0.083***	-0.015*	-0.054***	-0.007	-0.056***	0.003	-0.1***	0.022***	-0.213***	0.023**
	(0.019)	(0.009)	(0.010)	(0.005)	(0.011)	(0.006)	(0.014)	(0.009)	(0.026)	(0.012)
$5YearTerm_{it}$	0.098***	-0.174***	-0.043***	-0.315***	-0.223***	-0.496***	-0.373***	-0.471***	-0.282***	-0.16***
	(0.023)	(0.012)	(0.013)	(0.008)	(0.014)	(0.009)	(0.019)	(0.013)	(0.035)	(0.017)
Issued YQ_{it}	0.001	-0.011	0.026***	-0.014***	-0.038***	-0.018***	-0.088***	0.052***	-0.446***	-0.023***
	(0.014)	(0.007)	(0.006)	(0.003)	(0.007)	(0.004)	(0.009)	(0.005)	(0.026)	(0.008)
Credit $Grade_{it}$	0.212***	-0.001	0.217***	0.023***	0.299***	0.006**	0.338***	0.057***	0.472***	0.117***
	(0.01)	(0.005)	(0.005)	(0.003)	(0.006)	(0.003)	(0.009)	(0.005)	(0.019)	(0.006)
Intercept	7.774***	7.35***	7.637***	7.28***	7.702***	7.56***	8.2***	7.065***	10.493***	6.935***
	(0.162)	(0.078)	(0.092)	(0.049)	(0.094)	(0.05)	(0.137)	(0.079)	(0.282)	(0.108)
Gamma	1.599***	1.716***	1.509***	1.596***	1.229***	1.423***	1.458***	1.666***	1.486***	2.724***
	(0.025)	(0.014)	(0.013)	(0.012)	(0.009)	(0.007)	(0.037)	(0.038)	(0.056)	(0.085)
LogSig	-39.255***		-7.394		-4.124***		-0.12***		0.35***	
	(0.001)		(13.540)		(0.986)		(0.029)		(0.009)	
Observations	21,321		68,870		95,794		80,209		105,350	
Log Likelihood	-261,338		-809,834		-985,424		-580,665		-271,867	

Table 8. LendingClub Selection parameters included in Outcome Estimation

This table reports hazard ratios for two types of loan termination, default and prepayment, for loans originated on LendingClub during the period 9/21/2014 - 12/31/2016. Hazard ratios greater than one suggest the variables have a positive association with default while ratios less than one have a negative association with default. We estimate a Cox proportional hazard model for default in columns (1) and (2), and prepayment in columns (3) and (4). Columns (1) and (3) use the full sample of loans. Columns (2) and (4) use loans originated from September 2014 to May 2016. As suggested by Heckman (1979), we include the linear terms of the selection equation (*RiskScore*) in the model to yield unbiased coefficients in the outcome estimation. All the models contain indicators for credit grade and loan purpose. The models also contain quarter-year fixed effects. The z statistics are reported in parentheses. "***", "**", and "*" denote statistical significance at the 1%, 5%, and 10% level respectively.

	$Default_{it}$		$Prepayment_{it}$	
Sample Period	All	Before May 2016	All	Before May 2016
	(1)	(2)	(3)	(4)
$Whole_{it}$	0.969***	0.973***	0.989*	0.996
	(-3.22)	(-2.71)	(-1.75)	(-0.68)
$Inq6Month_{it}$	1.095***	1.094***	1.056***	1.059***
	(20.23)	(19.44)	(17.09)	(16.97)
$YrsFirstCredit_{it}$	0.994***	0.993***	0.996***	0.996***
	(-10.22)	(-10.58)	(-10.29)	(-10.84)
$Utilization_{it}$	0.987***	0.987***	0.985***	0.985***
	(-16.87)	(-16.17)	(-31.60)	(-30.26)
$Utilization_{it}^2$	1.000***	1.000***	1.000***	1.000***
	(12.01)	(11.39)	(17.31)	(16.57)
$Amount_{it}$	1.125***	1.116***	0.966***	0.971***
	(15.07)	(13.67)	(-7.41)	(-5.94)
$IntRate_{it}$	1.341***	1.340***	1.123***	1.147***
	(20.84)	(19.28)	(15.77)	(15.90)
$IntRate_{it}^2$	0.996***	0.996***	0.999***	0.998***
	(-11.23)	(-9.75)	(-5.46)	(-7.81)
$5YearTerm_{it}$	0.681***	0.688***	0.621***	0.610***
	(-33.10)	(-31.34)	(-59.14)	(-58.49)
$EmployLen_{it}$	0.982***	0.983***	1.014***	1.013***
	(-15.16)	(-14.40)	(18.20)	(15.97)
DTI_{it}	1.000***	1.000***	0.987***	0.987***
	(3.93)	(4.15)	(-39.30)	(-37.29)
$RiskScore_{it}$	0.957***	0.955***	1.069***	1.062***
	(-12.16)	(-12.38)	(34.43)	(29.06)
$CreditGrade_{it}$	All	All	All	All
Loan $Purpose_{it}$	Yes	Yes	Yes	Yes
Time Fixed Effect	Year-Qtr	Year-Qtr	Year-Qtr	Year-Qtr
Observations	761,816	547,486	837,140	614,059

Table 9 Adverse Selection in the LendingClub Institutional (Whole) Loan Market

This table reports default hazard ratios for loans originated on LendingClub during the period 9/21/2014 – 4/30/2016. Hazard ratios greater than one suggest the variables have a positive association with default while ratios less than one have a negative association with default. We estimate a Cox proportional hazard model for default. Column (1) models the full sample of loans. Splitting the sample by credit grade, the table reports hazard ratios for investment grade (IG) loans in column (2) and riskier high yield (HY) loans in column (3). We include an indicator for loans that are initially assigned to the whole (institutional) loan market but fail to be funded and roll over to the fractional market (*W/F*) for funding. *W/W* is an indicator for loans that are initially allocated to the whole loan market and are funded in the whole loan market. The omitted base case (*F/F*) are loans that are initially allocated to the fractional (retail) market and funded in the fractional market. We also include an indicator for low adverse selection, *HighRollover*, equal to one when the rollover ratio is greater than its sample median. All the models contain indicators for credit grade, debt-to-income (DTI) quartile, and loan purpose. The models also contain quarter-year fixed effects. The chi-squares statistics are reported in parentheses. "***", "**", and "*" denote statistical significance at the 1%, 5%, and 10% level respectively.

	(1)	(2)	(3)
W/F_{it}	1.029	0.975	1.076*
	(0.66)	(0.22)	(2.67)
W/W_{it}	0.972***	0.988	0.953***
	(7.22)	(0.67)	(10.47)
$HighRollover_{t}$	0.996	0.998	0.994
	(0.09)	(0.00)	(0.11)
$HighRollover_{t} \times W/F_{it}$	0.928*	0.982	0.87***
	(3.44)	(0.08)	(6.92)
$Inq6Month_{it}$	1.104***	1.119***	1.094***
	(419.50)	(210.73)	(210.10)
$YrsFirstCredit_{it}$	0.99***	0.993***	0.987***
	(192.39)	(54.39)	(152.92)
$Utilization_{it}$	0.988***	0.988***	0.988***
	(220.51)	(114.88)	(107.1)
$Utilization_{it}^{2}$	1.008***	1.009***	1.007***
	(110.00)	(68.92)	(42.74)
$Amount_{it}$	1.121***	1.071***	1.186***
	(183.52)	(35.88)	(186.7)
$IntRate_{it}$	1.355***	1.535***	1.208***
	(363.86)	(123.96)	(21.51)
$IntRate_{it}^{2}$	0.995***	0.99***	0.998*
	(99.72)	(38.34)	(3.59)
$5YearTerm_{it}$	0.677***	0.641***	0.705***
	(1002.0)	(583)	(426.40)
$EmployLen_{it}$	0.986***	0.983***	0.987***
	(123.24)	(81.12)	(49.18)
$CreditGrade_{it}$	All	IG	HY
DTI $Level_{it}$	Yes	Yes	Yes
Loan $Purpose_{it}$	Yes	Yes	Yes
Time Fixed $Effec_{t}$	Year-Qtr	Year-Qtr	Year-Qtr
Observation	500,287	376,084	124,203

Table 10 Preferential Assignment on LendingClub Driven by Adverse Selection

This table reports default hazard ratios for loans originated on LendingClub during the period 9/21/2014 – 12/31/2016. Hazard ratios greater than one suggest the variables have a positive association with default while ratios less than one have a negative association with default. We estimate a Cox proportional hazard model for default. Column (1) models the full sample of loans. Splitting the sample by credit grade, the table reports hazard ratios for investment grade (IG) loans in column (2) and riskier high yield (HY) loans in column (3). We include the lagged rollover ratio, *Rollover*, as a proxy for adverse selection in the institutional market. All the models contain indicators for credit grade and loan purpose. The models also contain quarter-year fixed effects. The z statistics are reported in parentheses. "***", "**", and "*" denote statistical significance at the 1%, 5%, and 10% level respectively.

		All	
	(1)	(2)	(3)
$Whole_{it}$	0.935***	0.913***	0.951*
	(-3.46)	(-3.23)	(-1.81)
$Rollover_{t-1}$	1.134	0.970	1.225
	(1.09)	(-0.17)	(1.30)
$Whole_{it} \times Rollover_{t-1}$	1.358**	1.923***	1.003
	(2.18)	(3.17)	(0.02)
$Inq6Month_{it}$	1.100***	1.113***	1.092***
	(21.38)	(14.95)	(15.33)
$YrsFirstCredit_{it}$	0.994***	0.997***	0.990***
	(-10.44)	(-3.82)	(-11.21)
$Utilization_{it}$	0.989***	0.989***	0.990***
	(-14.09)	(-10.02)	(-9.94)
$Utilization_{it}^2$	1.000***	1.000***	1.000***
	(9.88)	(7.56)	(6.37)
$Amount_{it}$	1.109***	1.054***	1.181***
	(13.45)	(5.02)	(14.62)
$IntRate_{it}$	1.357***	1.517***	1.198***
	(21.75)	(11.85)	(5.21)
$IntRate_{it}^2$	0.995***	0.991***	0.998**
	(-11.91)	(-6.36)	(-2.17)
$5YearTerm_{it}$	0.671***	0.632***	0.697***
	(-34.55)	(-26.46)	(-22.72)
$EmployLen_{it}$	0.982***	0.978***	0.986***
	(-15.04)	(-13.11)	(-8.58)
DTI_{it}	1.000***	1.000***	1.000*
	(3.70)	(3.78)	(1.87)
$CreditGrade_{it}$	All	IG	HY
Loan $Purpose_{it}$	Yes	Yes	Yes
Time Fixed Effect	Year-Qtr	Year-Qtr	Year-Qtr
Observations	746,353	568,560	177,793

Table 11. Preferential Assignment on Prosper Driven by Clientele Effects

This table reports default hazard ratios for loans originated on Prosper during the period 3/25/2013 - 12/31/2017. Hazard ratios greater than one suggest the variables have a positive association with default while ratios less than one have a negative association with default. We estimate a Cox proportional hazard model for default. *Quiet* is an indicator equal to one for the period 2016 Q2 to 2017 Q1 when securitization activity was drastically scaled back. Column (1) uses the full sample of loans. Column (2) uses all of the loans up to the end of 2017 Q1. Column (3) uses all the loans from 2016 Q2 through 2017 Q4. All the models contain indicators for credit grade, debt-to-income (DTI) quartile, and loan purpose. The models also contain quarter-year fixed effects. The chi-square statistics are reported in parentheses. "***", "**", and "*" denote statistical significance at the 1%, 5%, and 10% level respectively.

	Full (1)	Pre 2017Q2 (2)	Post 2016Q1 (3)
$Whole_{it}$	1.052***	1.053***	1.047
	(7.34)	(7.41)	(0.47)
Quiet	763.823	280.635	0.853**
	(0.07)	(0.13)	(4.54)
Quiet × $Whole_{it}$	0.877***	0.876***	0.911
	(10.12)	(10.25)	(1.52)
$Inq6Month_{it}$	1.094***	1.094***	1.1***
	(674.64)	(674.21)	(178.35)
$YrsFirstCredit_{it}$	0.989***	0.989***	0.992***
	(284.53)	(287.41)	(42.43)
$Utilization_{it}$	0.995***	0.995***	0.997
	(35.31)	(35.71)	(2.70)
$Utilization_{it}^2$	1.002**	1.002**	1.000
	(5.50)	(5.70)	(0.07)
$Amount_{it}$	1.125***	1.124***	1.184***
	(206.2)	(203.62)	(100.12)
$IntRate_{it}$	1.181***	1.182***	1.153***
	(186.59)	(187.94)	(31.27)
$IntRate_{it}^2$	0.998***	0.998***	0.999**
	(29.93)	(30.79)	(4.76)
$5YearTerm_{it}$	0.703***	0.703***	0.684***
	(1002.6)	(1001.3)	(257.95)
$EmployLen_{it}$	0.987***	0.987***	0.986***
	(93.19)	(91.97)	(25.28)
$CreditGrade_{it}$	All	All	All
DTI $Level_{it}$	Yes	Yes	Yes
Loan $Purpose_{it}$	Yes	Yes	Yes
Time Fixed Effect	Year-Qtr	Year-Qtr	Year-Qtr
Observation	169,143	167,768	73,693

Table 12. Preferential Assignment on Prosper Driven by the Freedom to Assign

This table reports default hazard ratios for loans originated on Prosper during the period 3/25/2013 - 12/31/2017. Hazard ratios greater than one suggest the variables have a positive association with default while ratios less than one have a negative association with default. We estimate a Cox proportional hazard model for default. We proxy the freedom of the Prosper platform to assign loans with *FracPercent*, the weekly percentage of loans assigned to the fractional market relative to the total loan origination volume within the same credit grade, in columns (1) – (3) and *HighFreedom*, an indicator equal to one if *FracPercent* is larger than the first quartile, in columns (4) – (6). Columns (1) and (4) model the full sample of loans. We then split the sample by credit grade and report hazard ratios for investment grade (IG) loans in columns (2) and (5) and riskier high yield (HY) loans in columns (3) and (6). All the models contain indicators for credit grade, debt-to-income (DTI) quartile, and loan purpose. The models also contain quarter-year fixed effects. The chi-square statistics are reported in parentheses. "***", "**", and "*" denote statistical significance at the 1%, 5%, and 10% level respectively.

	Default$_{it}$					
	(1)	(2)	(3)	(4)	(5)	(6)
Whole$_{it}$	1.020	1.086**	0.992	1.023	1.068*	1.010
	(0.87)	(4.25)	(0.09)	(1.51)	(3.30)	(0.20)
FracPercent × Whole$_{it}$	1.019	0.888	1.090			
	(0.05)	(0.46)	(0.90)			
HighFreedom$_{t}$				1.003	1.036	0.987
				(0.00)	(0.14)	(0.05)
HighFreedom$_{t}$ × Whole$_{it}$				0.999	1.000	0.987
				(0.00)	(0.00)	(0.06)
Inq6Month$_{it}$	1.094***	1.121***	1.085***	1.094***	1.121***	1.085***
	(664.93)	(267.1)	(399.01)	(663.52)	(267.81)	(397.62)
YrsFirstCredit$_{it}$	0.99***	0.989***	0.99***	0.99***	0.989***	0.99***
	(274.83)	(110.30)	(153.90)	(272.46)	(108.88)	(152.99)
Utilization$_{it}$	0.995***	0.994***	0.996***	0.995***	0.994***	0.996***
	(35.72)	(21.81)	(14.72)	(35.25)	(21.29)	(14.73)
Utilization$_{it}^2$	1.002**	1.004***	1.001	1.002**	1.003***	1.001
	(5.94)	(7.52)	(0.76)	(5.73)	(7.26)	(0.74)
Amount$_{it}$	1.127***	0.979	1.221***	1.127***	0.980	1.221***
	(210.3)	(2.38)	(363.08)	(210.2)	(2.30)	(363.12)
IntRate$_{it}$	1.181***	1.295***	1.128***	1.18***	1.294***	1.126***
	(182.29)	(41.45)	(42.09)	(181.75)	(40.83)	(41.60)
IntRate$_{it}^2$	0.998***	0.994***	0.999*	0.998***	0.994***	0.999*
	(28.82)	(12.23)	(3.29)	(28.27)	(11.83)	(3.10)
5YearTerm$_{it}$	0.703***	0.684***	0.712***	0.702***	0.683***	0.712***
	(989.22)	(316.49)	(650.48)	(992.52)	(318.91)	(651.01)
EmployLen$_{it}$	0.987***	0.988***	0.987***	0.987***	0.988***	0.987***
	(92.63)	(28.10)	(63.41)	(92.60)	(27.77)	(63.61)
CreditGrade$_{it}$	All	IG	HY	All	IG	HY
DTI Level$_{it}$	Yes	Yes	Yes	Yes	Yes	Yes
Loan Purpose$_{it}$	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effect	Year-Qtr	Year-Qtr	Year-Qtr	Year-Qtr	Year-Qtr	Year-Qtr
Observation	167,775	82,096	85,679	167,585	81,928	85,657