Do FinTech Lenders Fairly Allocate Loans Among Investors? *Quid Pro Quo* and Regulatory Scrutiny in Marketplace Lending

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Abstract

Marketplace lending platforms select which investors will have the opportunity to fund loans. Platforms claim to fairly allocate loans between retail and institutional investors, but we provide evidence that contradicts this claim. Institutional investors are allocated loans with lower default rates after controlling for interest rates, consistent with a *quid pro quo* exchange for volume commitments. However, when regulators are most likely to monitor the platform, we find that institutional-investor favor wanes, and platforms redirect lower default rate loans to retail investors. The evidence suggests platforms adjust allocation behavior to avoid costly regulatory intervention.

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Recent technological advancement has created new paths to match investors with those seeking capital. Through technology, a wider swath of investors, both retail and institutional, can participate in capital provision and a broader set of entrepreneurs, individuals, and firms can seek capital. These innovations can be seen across capital markets: marketplace lending platforms create debt contracts, crowdfunding platforms facilitate equity underwriting, and most recently, decentralized autonomous organizations (DAOs) issue digital tokens and cryptocurrency. While the expanding opportunities created by financial technology (FinTech) entities for those seeking capital is an important issue (Buchak et al., 2018; Tang, 2019), we focus on the impact of the broadening of the investor base in this paper. Using one of the most mature FinTech segments, marketplace lending, we examine financial technology platform behavior when diverse investors participate.

Marketplace lending platforms (MLPs) facilitate the creation of debt contracts for borrowers by attracting investors to the platform and matching them with a particular loan request. Traditional institutions such as commercial banks and hedge funds provide capital for the loans, but retail investors also fund loans through the platform. The MLP decides which loans will be sent to each group for funding. This allocation decision is akin to the decision performed by asset underwriters in corporate equity/debt. The literature on security initial public offerings (IPOs) suggests that larger/consistent capital providers are likely be favored in such a setup (Cai et al., 2007; Cornelli and Goldreich, 2001; Fang, 2005; Hanley and Wilhelm, 1995).

The FinTech platform setting adds two novel twists. First, marketplace lending platforms explicitly claim fair allocation among investor groups.[1] In multiple regulatory filings, MLPs claim that loan requests are fairly allocated between retail and institutional investors. Second, U.S. marketplace lending platforms born during the financial crisis experienced an abnormal amount of regulatory scrutiny during their formative years. Within the first three years of operation, both major U.S. MLPs were closed by regulators for extended periods (6–9 months), fined, and subjected to both federal and state security regulatory

[1] In this context, fair allocation implies that given a loan interest rate, contracts assigned to retail investors and institutional investors should have identical expected default rate, or vice versa. It does not imply "correct" pricing—that is, interest rates priced commensurate with systematic risk. The platform may unintentionally (intentionally) price a loan incorrectly, but should nonetheless fairly distribute contracts among investors.

oversight, unable to find exemption at either level because of their unique design. One result of this early regulatory scrutiny is that MLPs may engage in substantially different behavior than traditional underwriters, similar to Kubick et al.'s (2016) findings on tax avoidance behavior of firms following a regulatory intervention. In light of these unique features of marketplace lending, our objective in this paper is to investigate whether securities are fairly allocated between retail and institutional investors in marketplace lending.

We first document that on average, loans allocated to institutional investors have similar default rates relative to those allocated to retail investors. Using multiple modeling approaches (Cox, Weibull, and Exponential) and various empirical specifications with rich borrower/loan-specific controls (including interest rates), we find weak evidence, if any, of unfair allocation in the average loan. We also verify that interest rates are fairly set for loans allocated to both groups of investors.[2] Thus, on the surface, marketplace lending platforms appear to comply with their stated practice of fair allocation.

From the IPO literature, it is clear that certain investors are favored by underwriters in the security allocation process (Jenkinson et al., 2018). As institutional investors demand more loans and become more prominent providers of capital on the lending platform, they might exercise market power to seek preferential treatment in exchange for future volume commitments. However, periods of high loan demand by institutional investors may engender additional regulatory scrutiny, and MLPs may reduce *quid pro quo* favorable allocation. Evidence from after the financial crisis suggests that increased demand for mortgages corresponded with a monotonic decrease in loan quality (Demyanyk and Van Hemert, 2011; Mian and Sufi, 2009). In later tests, we verify a similar correlation between loan quality and institutional loan demand on the MLP even after controlling for observable borrower characteristics and credit grade. If regulators are sensitive to such a relationship following the financial crisis, then given the large volumes of data MLPs report to federal regulators on a daily basis, heavy institutional investor demand may also coincide with a higher probability of regulatory monitoring. If an increase in loan demand corresponds with an elevated

[2] See Appendix Table A1

risk of regulatory scrutiny, platforms may curtail *quid pro quo* behavior favoring institutional investors during such periods.

Consistent with the *quid pro quo* channel, our tests show that during periods of low institutional investor demand, institutional investors are assigned loans with a lower default rate than the loans assigned to retail investors. We conservatively estimate the difference in default rate as 8.4% lower; however, depending on the specification, we find differences as high as 20.8% lower. Because we estimate hazard models conditioned on length of survival and control for interest rates, in real terms, a lower default rate in this range should translate to a net return wedge of roughly 27–66 basis points (BP) given the average interest rate and default rate of the sample.[3] However, we show that the favorable allocation of lower defaulting loans is dampened during periods of high institutional demand, consistent with the regulatory scrutiny channel. During such periods, default rates for loans assigned to institutional investors increase by 5.8%. Unexpectedly, we find that loan default rates for retail investors fall during high institutional loan demand periods. This result is consistent with firm behavior observed in Kubick et al. (2016), which finds that firms that once engaged in aggressive tax-avoidance behavior relative to their peers took part in less tax-avoidance behavior than their peers after regulatory intervention. The propensity to allocate lower defaulting loans to retail investors during periods of high loan demand to ensure regulatory compliance is consistent with firms that experience high costs for regulatory non-compliance such as platform closure.

The results favoring the regulatory scrutiny channel are robust to multiple concerns. Using rejected loan applications, we show that the regulatory scrutiny results hold when we incorporate the platform credit screen as a first-stage selection process prior to the hazard model (similar to Heckman (1979) selection concerns for linear models). We also conduct multinomial-logit competing-hazard tests to ensure sample selection driven by prepayment activity does not alter our results. We demonstrate a similar regulatory scrutiny effect on a competing platform. Finally, we take advantage of an exogenous shock to regulatory

[3] Our back of the envelope estimate assumes the sample average 23.56% default rate, a 13.45% interest rate, defaulting loans make no payments, and a default difference of 8.4%. This should translate to a net return difference of 27 BP.

monitoring on the platform to show the MLP adjusts allocation behavior even after removing the influence of shifting institutional investor demand.

Our results imply that while institutional investors receive some preferential treatment during periods of low institutional loan demand, when institutional loan demand is high, the aggregate quality of loans allocated to institutions deteriorates. If institutional investors are conscious of this quality decline, why continue to invest on the platform? Alternatively, why would the platform pursue such a strategy given the risk that institutional investors may leave as a result? While it is possible some or all institutional investors may be unaware of the quality shift, we believe it is more plausible that they willingly accept the quality/quantity tradeoff from the platform, for two reasons. First, if outside opportunities on other MLPs are limited by a similar inability to increase origination volume while holding loan quality constant, which we show with a competing platform, institutional investors have little incentive to leave for another platform. Second, as shown by Kräussl et al. (2018), asset returns from MLP loans are relatively high and uncorrelated with systemic risk factors typically used to price equity/debt assets. Thus, institutional investors may willingly accept the quality decline to achieve a certain quantity of loans. Also, as we'll show later in Section 5.1, a large fraction of institutional investors are also asset-backed security (ABS) issuers on our MLP under study. ABS investors that pool and securitize loans may be less sensitive to a quality/quantity tradeoff if they have little "skin in the game."

Analyzing the behavior of marketplace lending platforms and understanding their incentives are important for three reasons. First, both the size and scope of these emerging intermediaries are economically significant. By 2017, the major marketplace lending platforms expanded to originate nearly a third of the personal unsecured loans in the United States.[4] Additionally, the incorporation of retail and institutional capital to fund loans is common across other large MLPs like Prosper (U.S.), Funding Circle (U.K.),

[4] Unsecured personal loan volume statistics come from TransUnion. MLPs have also broadened into automotive financing, residential mortgages, small business lending, and student loan financing. Buchak et al. (2017) show that in the residential mortgage market, FinTech lenders increased their market share of originations from 3% in 2007 to 12% in 2015. Fuster et al. (2019) show a similar rise in residential mortgage originations by FinTech platforms from 2010 to 2016.

Paipaidai (China), China Rapid Finance (China), LendingLoop (Canada), Auxmoney (Germany), and Lendico (Germany), among others. While we focus on the U.S. market because of its transparency and data availability, the number of FinTech lending platforms in the U.S. is relatively low compared to developing markets like China, where there are hundreds of such platforms (Jiang et al., 2019). We anticipate the impact of FinTech growth may play an even more significant role in these markets. Verifying the behavior and understanding the incentive mechanisms of MLPs with such size and scope would appear to be of first-order importance.

Second, the new structural features of FinTech platforms may generate behaviors not observed in traditional financial markets (Vallee and Zeng, 2018). The platforms' incorporation of both retail and institutional investors combined with the pricing of loan contracts independent of investor information is a novel structure. Compare this structure to the typical corporate debt/equity IPO. The book-building mechanism in debt/equity IPOs is traditionally used to facilitate a *quid pro quo* exchange of information, service, or volume commitment for preferential allocation of underpriced security issues (Aggarwal et al., 2002; Cornelli et al., 2006; Dorn, 2009; Neupane and Poshakwale, 2012). In contrast, the structure of marketplace lending strips out many of the typical underwriter incentives: information provision by investors is irrelevant because of the platform's pricing model (Benveniste and Spindt, 1989; Hanley and Wilhelm, 1995), and to our knowledge platforms offer no post-offering services for borrowers or investors (Jenkinson et al., 2018). One of our main contributions is to provide evidence consistent with a *quid pro quo* interaction between platforms and institutional investors, similar to IPO underwriting (Ljungqvist and Wilhelm, 2002). At the same time, our work is novel because we show an additional channel that platforms preferentially allocate loans to retail investors in response to elevated regulatory scrutiny. Through the marketplace lending environment, we are able to show the lasting effect of heightened regulatory intervention on FinTech emerging during the financial crisis and the importance of new research into FinTech platform behaviors and incentives.

Finally, because these organizations are in their infancy, documenting their behavior and their underlying incentives is important to establishing a proper regulatory structure. An overly burdensome regulatory approach can easily stifle the innovativeness of the platforms or incent them to conduct regulatory arbitrage activities (Venkatesan et al., 2018); an approach that is too light handed exposes investors to substantial risk. For example, Jackson, Squire, and Honigsberg (2016) find that marketplace lending loans issued in the second circuit may be considered null and investors may hold notes that are not enforceable in the event of default. Understanding FinTech platforms' incentives would seem to be a critical first step toward identifying optimal policies to regulate them.

In examining FinTech platform behavior and incentives, this paper connects the growing FinTech literature with the financial intermediation literature on IPO underwriting and originate-to-distribute banking models. The literature on FinTech credit firms such as marketplace lending platforms is in its infancy but continues to expand. Early research on marketplace lending focused on retail investor behavior during the period 2006 to 2013 when the majority of investors on the platforms were retail investors. These studies show that retail investors have a bias toward borrower beauty (Ravina, 2019) and geographic region (Hornuf and Schmitt, 2016; Lin and Viswanathan, 2016; Senney, 2016). Investors tend to herd (Hildebrand et al., 2017; Zhang and Liu, 2012) but also learn over time (Lin et al., 2015). Later work examines how platforms expand over time (Fuster et al., 2019; Havrylchyk et al., 2016), whether borrowers use online credit access to circumvent regulatory restrictions (Braggion et al., 2019), whether FinTech adoption is driven by borrower impatience (Maggio and Yao, 2018), and whether FinTech lenders expand credit access or substitute for commercial lending volume (Buchak et al., 2018; Cornaggia et al., 2018; de Roure et al., 2016; Tang, 2019). Our paper is unique in that it examines the behavior of marketplace lending platforms and abstracts from borrower behavior and the impact on credit markets.

In contrast to the growing FinTech literature, the IPO literature on underwriting is a richly developed topic. Lowry et al. (2017) and Loughran and Ritter (2004) provide an excellent overview of the subject. Marketplace lending platforms' compensation is extracted through fees charged to borrowers (origination fees) and investors (service fees), and these fees are proportional to the volume of origination. In this sense, they share a common objective with IPO underwriters (Jenkinson et al., 2018). Multiple factors may contribute to IPO underwriter behaviors such as underpricing and preferential allocation, but most accepted models are motivated through a *quid pro quo* relationship between agents to resolve information asymmetry. In some cases the exchange resolves friction between issuer and underwriter (Baron, 1982; Beatty and Welch, 1996; Loughran and Ritter, 2004, 2002; Welch, 1989) and in others between underwriter and investor (Benveniste and Spindt, 1989; Sherman, 2000; Sherman and Titman, 2002). A common theme among the latter is the use of underpricing (Cai et al., 2007; Cornelli and Goldreich, 2001; Fang, 2005; Hanley and Wilhelm, 1995) to compensate large investors to smooth their consumption of hot and cold IPO issues and promote information sharing. Because the marketplace lending paradigm differs from the traditional IPO setting, our exercise is simplified: investors can only be rewarded through the allocation of lower defaulting loans and platforms only seek to boost loan volume. Our results suggest a similar *quid pro quo* exchange between institutional investors and the platform and highlight an additional channel not observed in the IPO literature.

The structure of marketplace lending also resembles originate-to-distribute (OTD) models of intermediation. Purnanandam (2011), Keys et al. (2010), and Keys et al. (2012) discuss the reduction in the underwriter's incentives to collect private (soft) information on borrowers during the mortgage screening process when the underwriter distributes a large portion of the loans underwritten. Further, Rajan et al. (2010, 2015) model and empirically show that mortgage lenders during the financial crisis had incentives to change the quality of hard information embedded in pricing signals. By design, marketplace lenders attempt to distribute all the loans originated. The only exception to this design occurs when, beginning in 2017, loans are originated within (internal) securitization programs sponsored by the marketplace lending platform.[5] In the robustness section, we examine the difference between loans issued during internally issued ABS programs and ABS periods backed by other financial intermediaries. However, we find no difference in loan quality. Despite our absence of findings, it remains the case that the design of marketplace

[5] Implementation of the Dodd–Frank Wall Street Reform and Consumer Protection Act credit risk retention rules in December 2016 appears to have shifted external asset-backed securitization activity to ABS issued exclusively by the marketplace lending platform.

lending mirrors the design of the OTD models of intermediation and its incentive is structured in a way to encourage similar behavior.

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 Kingdom and spread to the United States with the creation of the first lending platforms in 2006. At the onset, platforms connected individual borrowers with *retail* investors. This led the industry to be known as peer-to-peer (P2P) lending. A peer-to-peer structure was maintained until 2012–2013 when the major U.S. platforms, LendingClub and Prosper, began to adopt additional features to attract more institutional investor capital. For example, both platforms opened a second funding market dedicated to institutional investors in early 2013. With the inclusion of institutional investors, who now provide a large portion of the capital, the process was renamed marketplace lending by most industry participants.

We present an overview of the current 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 from one of the major credit bureaus. The platforms screen credit applications using this hard information (Figure 1 (1)) without incorporating soft information that could be obtained through conversations a loan officer has with a borrower. After passing the initial credit screening, the borrower’s loan request is allocated to either the institutional or retail markets for funding by investors. This allocation decision is our main variable of interest.

Within the institutional funding market, investors have the ability to invest passively in loans held in a pool (Figure 1 (2)) or actively select particular loans (Figure 1 (3)). The passive funding pool is a subset of loans diverted away from the active markets based on prearranged institutional investment contracts and passive investment vehicles provided by the platform. Retail investors may only actively invest in loans (Figure 1 (5)). The loans allocated to the active funding markets (retail and institutional) are listed for funding in blocks at regular intervals (6:00 a.m., 10:00 p.m., 2:00 p.m., etc.). Investors race to commit to funding the loans (Balyuk and Davydenko, 2018), and many loans are funded within the first 60 seconds.

Before 2012, marketplace lending platforms consisted of one combined active funding market and a passive funding market. In this early period, most investors were retail investors. Active investors fractionally funded 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, marketplace lending platforms diverted institutional investors to their own funding market. This second market, known as the whole loan market, required investors to fund loans in their entirety as opposed to the fractional funding market for retail investors. As a result of this dual market structure, platforms were forced to make an allocation decision between the investor groups. That is, the platform must choose to initially place a borrower loan request either in the whole loan market for institutional investors to fund or in the fractional loan market for retail investors to fund. Currently, both of the largest U.S. marketplace lending platforms that allow retail and institutional investment state that the allocation of loans between these markets is random.[6]

In some cases, the platforms allow unfunded loans in the institutional active funding market to be reallocated into the retail active funding market (Figure 1 (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 up to 24 hours to fund loans before they are reallocated. This practice of reallocation occurs on platforms such as Funding Circle (Mohammadi and Shafi, 2017), Prosper (Balyuk and Davydenko, 2018), and LendingClub which is the MLP used in the

[6] LendingClub: https://help.lendingclub.com/hc/en-us/articles/115009000328-How-LendingClub-balances-different-investors-on-its-platform; see also LendingClub Asset Management, LLC CRD# 155460 ADV part 2 brochure dated 12/28/16, which we obtained via FOIA request from the SEC. Prosper: https://www.sec.gov/Archives/edgar/data/1416265/000156459016015019/prosper-10k_20151231.htm

current study. Retail (fractional) investors have 7–10 days to fund loans. On LendingClub, however, loans that fail to garner full retail funding are funded by the platform (Figure 1 (6)), meaning that after passing the credit screen on the platform, borrowers are guaranteed funding.

2. Hypothesis Development

In the equity IPO literature, asset allocation is one way of rewarding investors for providing costly information to underwriters so they can accurately price the asset (Aggarwal et al., 2002; Goldstein et al., 2011). While our focus in the current paper is not on the pricing of securities, we do verify that loan contracts assigned to retail and institutional participants are identically priced based on loan/borrower details. This implies that marketplace lending platforms price the debt contracts independent of allocation. Thus, marketplace platforms may allocate loans that are similarly priced but with lower expected default rates as a *quid pro quo* tool to encourage investors to fund loans. This suggests our first testable hypothesis:

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

Cornelli and Goldreich (2001) show that in equity IPO markets, repeat investors that regularly provide capital are more likely to be awarded shares of (favorable) oversubscribed IPOs. Ljungqvist and Wilhelm (2002) model and test the idea that such discretionary allocation is optimal. Both suggest that the volume of asset demanded by investors influences the quality of the allocation received. Because information production in the sense of Benveniste and Spindt (1989) is not a way for investors to earn favorable allocations on marketplace lending platforms, we anticipate that through greater capital provision, investors may garner more favorable allocation.

On the other hand, Demyanyk and Van Hemert (2011) and Purnanandam (2011) show that leading up to the financial crisis increased demand for mortgages led to lax screening that resulted in an increase in loan default.[7] If MLPs are incapable of producing borrowers of similar quality with increased demand for loans, a similar increase in default rate may be observed in marketplace lending. Given pass-through bank quality concessions were most egregious during high (mortgage) loan demand periods, post-financial crisis regulators may be sensitive to such concessions and increase monitoring. For example, federal regulators intervened in the leveraged loan market in 2013 as it became overheated, suggesting more rigorous monitoring of leveraged loan origination afterward.[8] MLPs report large volumes of data to federal regulators on a daily basis (Cornaggia et al., 2018), lowering the difficulty of supervising MLP behavior. Thus, if an increase in loan demand corresponds with an elevated risk of regulatory scrutiny, platforms may curtail *quid pro quo* behavior that favors institutional investors during such periods. We formalize this in our second hypothesis:

Hypothesis 2. *If platforms are insensitive to institutional investor demand, the hazard rate for default will not depend on the institutional demand for loans ($H2_0$). Alternatively, if institutional investors exert market power, then when institutional investor demand is high, the platform will allocate loans with lower expected default rates to institutional investors, ceteris paribus ($H2_{A1}$). Alternatively, if high institutional investor demand increases the likelihood of regulatory monitoring and costly intervention when institutional investor demand is high, the platform will allocate loans with higher expected default rates to the institutional investors group, ceteris paribus ($H2_{A2}$).*

3. Sample and Variable Construction

Our sample is composed of all "standard program" loans originated on the MLP LendingClub for the period 9/21/14 through 2017.[9] The standard program is LendingClub's prime (FICO>640) unsecured

[7] The motivation for a pass-through bank to reduce loan quality in Purnananadam (2011) is the cost of soft information production combined with the inability of the end investor to observe such information incorporation. In our setting, the bar may not be so high if institutional-investors are comfortable with the deterioration in loan quality is a necessary condition for loan volume and if the risk-adjusted returns are still substantial. Kraeussl et al. (2018) suggest that this may be the case.

[8] https://www.wsj.com/articles/SB10001424127887324373204578374763359396602

[9] LendingClub has two additional loan programs through which it originates loans. The first is an unsecured term loan program for subprime borrowers, i.e. borrowers who fall short of the standard loan qualifications on FICO or debt-to-income. This program is referred to as the "custom program" and is funded entirely by institutional

personal loan program. It encompasses all the prime loans funded by institutional and retail investors for standard loan purposes (debt consolidation, etc.) and represents the majority of LendingClub's loan origination (70%+). We match our loan volume data from the platform to the origination volumes listed in LendingClub's 10-k report to the SEC and find the numbers identical. For example, in the 2017 10-k, LendingClub reports a standard loan origination volume of $6.585 billion while the total of our loan data gives a loan origination volume of $6,584,957,000.

We gather three data sets from the platform. First, LendingClub provides a loan-issuance file that includes a unique loan identifier, details on the borrower's credit profile, and loan contract information for all standard program notes issued. LendingClub also identifies the initial funding market (fractional, whole) where the loan is allocated. From the loan-issuance file, we gather borrower credit information, the number of credit inquiries in the past six months, the number of years since first credit was established, credit-line utilization, debt-to-income ratio of the borrower, FICO score, and employment length. The loan-issuance file also captures loan details: the amount requested by the borrower, interest rate assigned by the platform to the loan, platform credit rating, term, and loan purpose. In order to identify reallocated loans (Figure 1 (4)), we augment details of the loan contracts provided by LendingClub with information publicly available through the Securities and Exchange Commission's (SEC) EDGAR database.[10] This also provides loan details that are omitted from the loan-issuance data, such as the date of a loan request.[11] The second set of data obtained from the platform provides loan outcomes. LendingClub provides data on loan status, which allows us to track the monthly progress of a loan. Using these data, we determine a loan's current/final status (default, prepaid, current, and complete/matured) and length of survival.[12] Third, we obtain rejection data from the platform that contains all loans rejected by the standard loan program (Figure 1 (1)). Included

investors. Loan purposes are similar to the standard program. The second is the "other loan" program, which focuses on prime borrowers seeking loans for nonstandard purposes such as education, patient financing, automotive refinancing, and small businesses. It is also funded exclusively by institutional investors. Data for these loans are not publicly available, although a large portion of the custom program notes are securitized and sold in asset-backed security offerings.

[10] See the Internet Appendix section IA1.3 for the identification procedure.

[11] In the files available from the platform, LendingClub only provides the month of origination.

[12] Our loan outcome data is a snapshot of the status of outstanding loans as of 8/3/18.

in the rejected-loan data are limited borrower attributes, such as FICO score, debt-to-income ratio, and state of residence, in addition to the size of the loan requested.

Marketplace lending loans are often funded by banks or hedge funds and securitized into an ABS. We gather securitization data 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 ABS issued with consumer loans from LendingClub as the asset pool. We then match the ABS data with information from the Kroll Bond Rating Agency (KBRA) 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. This methodology allows us to estimate when loans included in the pool were likely to be originated. Using this information, we calculate the ±30-day window around the origination date implied by the average loan age in the pool to serve as the period of time when institutional investors are most likely to be funding loans for ABS issue. We also collect data on the distribution of FICO scores within each ABS issue from KBRA.

In Table 1 Panels A and B, we present summary statistics for the loan sample. Following the literature on hazards/default (Lin et al., 2013), we create a sample of current and defaulting loans (Panel A). This allows us to separately compare loans "exiting" the sample for default with loans exiting for prepayment, which are materially different to an investor.[13] Panel B shows the composition of the sample for the loans allocated to the fractional and whole loan markets. On the surface, it would appear that retail investors (fractional market) are allocated a much higher fraction of the defaulting loans compared to whole-loan-funding markets. However, the summary statistics mask loan quality preferences: the institutional investors are allocated a significant fraction of the A, B, and C grade loans—difference that remain when we split the sample by funding market and credit grade (Table 2). Figure 2 compares

[13] Although the focus of our analysis is on default, we examine prepayment in the Internet Appendix section IA1.4.

default/prepayment rates for loans by subgrade across the two funding markets. In unreported results, we formally compare the default rate for each funding market (fractional/whole) by grade and find, for all credit grades, that the difference of default rates between two markets is statistically significant at the 1% level of significance. While there are multiple confounding factors that may explain these average differences, they hint at preferential allocation—something we confirm formally in Section 4.

It is possible that other loan/borrower characteristics influence the conditional default rate outside of the information contained in the credit grade. Additionally, the information implied by the credit grade may also be time-variant. Figure 3 shows that within each credit grade the fraction of loans assigned to the two markets varies considerably. For example, in 2014, approximately 48.2% of the A grade loans on LendingClub are assigned to the fractional market compared to 35.0% of the G grade loans. These preferences shift over time. By 2017, only 16% of the A grade loans are initially assigned to the fractional market while 25% of the G grade loans are initially allocated to the fractional market. To address these concerns, in the next section we formally test the difference in loan outcomes in a multivariate setting.

4 Empirical Results

4.1 Average Default

Our first objective is to test the assertion that loans are fairly assigned to retail and institutional investors. Figure 2 suggests that the marketplace lending platform selectively allocates loans with lower 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 if the proportion of observations in a particular credit-risk category are not evenly spread out over time, then it is possible that differences in the average default could be explained by 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.

Our loan data runs from the third quarter of 2014 through 2017.[14] Because the term of the loans is either three years or five years, very few of the loans in the sample will have the ability to mature, and our pool of observations will be right-censored on our variables of interest (default). To address this issue, 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 hazard for the different funding markets given the status of the loans when we collect the loan data.

We include borrower characteristics such as the number of inquiries in the last six months, years since credit was established, debt-to-income ratio, indicators for loan purpose, indicators for employment length, and credit utilization at the time of listing. We follow Lin and Viswanathan (2016) and incorporate the square of credit utilization. The specification also uses additional information on loan-contract features to describe the risk of default. We include the dollar amount of the loan request, the interest (coupon) rate on the loan, an indicator for the term of the loan, and indicators for the credit grade of the loan assigned by the platform. 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, an identifier for the funding market (whole or fractional) should not be associated with the default hazard 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, our specification for this test is:

$$h(t|\boldsymbol{x}) = h_0(t)\, exp(\boldsymbol{x}'\boldsymbol{\beta})$$

where $h(t|\boldsymbol{x})$ is the hazard rate of default—i.e., the conditional default rate—h_0 is the baseline hazard, and

$$\boldsymbol{x}'\boldsymbol{\beta} = \beta_t + \beta_{1,i} \times Whole_i + \boldsymbol{x}'_{borrower}\boldsymbol{\beta}_{\mathbf{2},i} + \boldsymbol{x}'_{loan}\boldsymbol{\beta}_{3,i}. \tag{1}$$

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

In Table 3 column (1), we make no assumption on the distribution of the hazard and nonparametrically estimate the hazard rate with a Cox proportional hazard model.

Table 3 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*, a statistically insignificant 0.991, suggests that loans allocated to the institutional market are indistinguishable from loans allocated to the fractional (retail) market in terms of default. Repeating the exercise with parametric versions of the model, we see similar hazard ratios of 0.991 in an Exponential model in column (2) and of 0.988 in a Weibull model in column (3). These would suggest institutional investors may be allocated loans with a slightly lower (0.90–1.25%) default rate. In the case of columns (2) and (3), though, the coefficients in the model are statistically significant at the 10% and 5% levels, respectively. Between the mixed significance of the hazard ratios and the economically small impact implied by columns (2) and (3), it is difficult to reject the null for Hypothesis 1 that loans are randomly allocated across the funding markets on the platform. In Section 4.2, we find conclusive evidence to reject the null for Hypothesis 1.

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. Including interest rates in the hazard function means we eliminate the possibility that while investors are allocated loans with higher default rates than predicted by observable characteristics, they are also paid a higher interest rate. Longer-term loans have a hazard ratio of less than one. Credit line utilization and interest rates have a nonlinear impact on the likelihood of default.

4.2 Institutional Investor Demand: *Quid Pro Quo* or Regulatory Scrutiny

While Table 3 demonstrates that the platform may fairly distribute loans on average, it is possible that preferential access to loans may change in the time series as institutional investor loan demand increases. Prior to 2013, almost all capital in the marketplace lending market was provided by retail investors. After the introduction of the whole loan markets, institutional investors supplied an increasingly large proportion of capital to originate loans on the platform (see Figure 3). This is especially true for investment-grade loans. According to the equity IPO literature, underwriters of equity IPOs preferentially allocate assets to institutional investors because of their depth of capital (Aggarwal et al., 2002). In the same way, we predict institutional investors will receive preferential treatment when their demand for loans is high relative to retail investors ($H2_{A1}$). As discussed in Section 2, high institutional loan demand could also encourage more regulatory oversight. If loan quality falls during periods of high institutional investor demand—a condition we demonstrate in Section 4.4—then increased institutional loan demand may result in a high probability of regulatory monitoring. MLPs may rationally reduce *quid pro quo* behavior during such periods ($H2_{A2}$).

To test Hypothesis 2, we calculate the daily dollar fraction of loans assigned to institutional (whole loan) investors.[15] We then create an indicator variable (*High W Fraction*) if this measure is above the sample median. It is by interacting the *Whole* indicator with *High W Fraction* that we test Hypothesis 2. The base group, in this setup, is the retail investors during periods of low institutional loan demand. In Table 4 column (1), institutional investors receive loans with a lower conditional default rate than the base group. When institutional investor demand is low, institutional investors are allocated loans with an 8.4% lower default rate than the loans allocated to retail investors. When institutional investor demand is high, the institutional investor hazard rate increases by 5.8% (0.872 * 1.213 = 1.058). The *High W Fraction* term also implies that retail investors are allocated loans with a 12.8% lower default rate during periods of high institutional loan

[15] Ideally, we would measure the desired loan demand—i.e., how much investors want to invest—of institutional investors, instead of the platform's estimate of loan demand. However, the platform's estimate is an appropriate proxy for three reasons. First, the desired loan demand of passive institutional investors should match with the platform's loan demand estimate because they must articulate their desire to the platform. For active institutional investors, we expect that the platform still regularly measures institutional investor loan demand, especially in the latter half of the sample when the reallocation rate of loans falls to nearly zero (Figure 1 (4)). Second, Balyuk and Davydenko (2018) suggest passive institutional investors are the majority of institutional capital on the competing platform Prosper, which would suggest a closer proxy if a similar institutional mix exists on LendingClub. Third, given the extremely high rejection rate (92%+) during the credit screen, and given that Table 5 Panel B reveals high FICO scores can be more likely to be rejected in the platform application screening process than moderate FICO scores, we view this market as constrained by loan demand. This would suggest that the observed capital allocation is near the desired loan demand.

demand. In other words, when institutional investors demand more loans from the platform, retail investors are allocated loans with substantially lower default rates.

We confirm these base results across multiple specifications. Using a daily aggregate amount ignores the idea that the platform may make short-term commitments to institutions and may behave in a smoother fashion toward institutional clients. If we substitute the daily fraction of institutional loan demand for a 30-day moving average (column 2) the results are consistent and intensify. If the platform is more concerned with whichever group is the majority capital provider, we might use the 50% mark as the breaking point for the indicator instead of the sample median, which is close to 72%. We show the results for this alternative breaking point in column (3) for the daily fraction and column (4) for the 30-day moving average. The results again are consistent and also intensify over our base results in column (1). If the platform is interested in the absolute volume of capital provided by an investor group instead of the fraction, it may be more appropriate to use the dollar amount of loans allocated to each group. In columns (5) and (6) we use the daily amount of loans demanded by institutions and obtain similar results. We also include alternative modeling approaches, using an Exponential hazard model in column (7) and a Weibull hazard model in column (8). The results are again consistent with column (1).

All of the results in Table 4 point to a similar theme: during periods of low institutional loan demand, institutional investors are allocated loans with lower default rates than the loans allocated to retail investors. However, during periods of high institutional loan demand, the allocation of loans to institutional investors deteriorates, and retail investors are allocated loans with substantially lower default rates. Based on these results, we reject the null hypothesis $H1_0$. This suggests we should also reject both the $H2_0$ and $H2_{1A}$ hypotheses in favor of the regulatory scrutiny channel $H2_{1B}$. However, it is also clear that during periods of low institutional demand, institutions do receive allocations with a lower default rate than retail investors. The results suggest that both the *quid pro quo* channel and the regulatory scrutiny channel influence the behavior of marketplace lending platforms. In Section 4.4, we address why retail investors may be allocated loans with lower default rates during high institutional-demand periods.

4.3 Robustness Tests: Endogenous Selection and Competing Hazards

Two econometric issues could potentially arise in the analysis. First, for the above sample of loans, we only observe outcomes for a portion of the loan applications. Borrowers apply for loans on the platform and the platform screens the initial applicant pool, only allowing certain loans to be presented to investors to fund. As described in Heckman (1979), restricting the sample to only funded loans could present a selection issue. For example, if information in the platform's loan-rejection decision were to influence the hazard rate of default and if the information is correlated with our explanatory variables in the outcome (default) model our coefficient estimates would be biased.[16] Such a selection issue could happen if the platform incorporates alternative (unobserved) information in the credit screening decision that would influence default rates and correlate with any of the borrower quality measures (credit grade, debt-to-income ratio, employment history, etc.).

To address this potential selection issue, we utilize a feature of the platform that allows investors to observe applications that do not pass the platform credit screen. The loan-rejection file described in Section 3 provides details for each application, including credit score, debt-to-income ratio, loan amount requested, and the length of employment of the applicant. Some of the loan requests are for loans outside the platform's Standard Program guidelines (loan amount >$35,000) or borrower restrictions (debt-to-income ratios over 0.35 or 0.40, depending on the time period). We filter out such rejected applications because they are not comparable loan applicants to the applicants receiving loans.[17] We also standardize credit scores, given the various credit-score models used by the platform.[18] Using these data, we conduct a two-stage hazard estimation similar to the linear outcome model used by Heckman (1979). Following the labor economics literature (Boehmke et al., 2006; Prieger, 2002), our first stage consists of a Probit model

[16] A second selection issue could occur if investors only fund a portion of the loans presented on the platform. Lin et al. (2016) address this issue on the Prosper platform when considering which loans are funded by investors. In the case of LendingClub, we are able to avoid this selection issue because all loans passing the initial platform credit screen are offered funding. Loans that are rejected by both active markets are backstopped by the platform, so all outcomes of loans that pass the credit screen are observed. We confirm this 100% funding rate with LendingClub.

[17] If such applications were included in the rejection sample, the platform screening process would be perfectly characterized by indicators of above/below debt-to-income cutoffs, etc. for these observations.

[18] See the variable definitions in the appendix for the standardization procedure.

that uses both the rejected loan applications and the accepted applications to estimate the probability that loans are selected by the platform. The model then parametrically estimates an exponential hazard ratio in a second stage, similar to the model presented in Table 4 column (7).

The results of the second stage are reported in Table 5 Panel A, columns (1)–(4). The first stage for columns (1)–(4) are reported in Table 5 Panel B, columns (1)–(4), respectively. The hazard ratios reported in column (1) for *Whole*, *High W Fraction*, and their interaction are statistically significant at the 1% level. The estimate of the inverse Fisher's Z (analogous to the inverse Mill's ratio) is also statistically significant, suggesting there may be some bias imparted by the selection process. However, comparing the hazard ratio estimate of the key variables of interest to Table 4 column (7), we see the degree of bias encountered because of selection to be minimal. For example, the coefficient on *Whole* in Table 4 column (7) is 0.9179, while in Table 5 column (1) it is 0.9544. This provides a certain measure of confidence that our results are robust to such selection concerns in later tests.

In Panel A column (2), we report the result of the second stage after using a modified selection equation that includes a term for the total loan supply (*Total Supply*) by applicants, employment history, and loan size request (selection equation in column (2) of Panel B). The results in Panel A column (2) are very similar to Panel A column (1). In the first-stage estimates in Panel B, applicants with an increasing credit score are more likely to pass the credit screen. However, this trend is nonlinear. For applicants with a credit score above 720, while they are more likely to pass the credit screen than the base group of 660–665, their likelihood of passing the credit screen decreases as their credit score increases. Higher debt-to-income ratios increase the likelihood of a loan application passing the credit screen. Both of these parameters suggest that in addition to screening for loan quality, the platform is also filtering applications based on indications of loan demand from investors. Increasing the loan amount requested by the borrower appears to decrease the likelihood of passing the credit screen. Though not reported in the table, an employment history greater than 12 months appears to be a strong condition for loan inclusion.

A second potential econometric issue is that in our specifications above, we exclude from the sample loans that are prepaid. While this approach follows the extant literature (Gross and Souleles, 2002;

Lin et al., 2013) it assumes prepayment is an independent random censoring mechanism when estimating default rates. However, it is likely that there is a negative correlation between defaults and prepayments (Clapp et al., 2006; Deng et al., 2000). If this is the case, it is possible our earlier tests are biased (Roberts and Whited, 2013). To show that the results are robust to such issues, we employ a multinomial logit model to incorporate the competing risk of prepayment, similar to Agarwal et al. (2012). We report the results in Table 6. Columns (1)–(2) use a quadratic baseline function, and columns (3)–(4) use a fifth-order baseline function following Gross and Souleles (2002). The relative risk ratio of default shown in column (1) for institutional investors during periods of low institutional investor loan demand is similar to our hazard ratio estimates, and it is statistically significant. This implies the *quid pro quo* relationship between institutions and the platform is robust to competing hazard concerns. As before, retail investors are allocated loans with a lower relative default rate during periods of high institutional loan demand, and institutional investor loan quality deteriorates during these periods. We obtain qualitatively similar estimates in column (3) with the fifth-order baseline hazard assumption.

Our argument of preferential allocation implies the platform holds private information not incorporated into the interest rate or credit rating. If this were not the case, the platform could not preferentially assign loans after controlling for interest rate and credit rating. Assuming the platform has incremental private information, it would seem to be most beneficial if that information is used to better price the loans (attracting more investors) or preferentially allocate loans (to attract certain investors). Private information could take the form of something simple, such as the distribution of expected default *within* a credit grade, or something complex, such as marginal information on utility payments or mobile phone activity. We do not believe this implies an omitted-variable problem. If the platform fairly/randomly allocates loans based on the "true" expected default rate, then credit rating, which is assigned based on a rank order of expected default, should still suffice as the mean value of the latent expected default. If the platform instead uses the additional private information for allocation purposes, our indicator of investor type (retail or institutional) would capture this private information. Vallee and Zeng (2019) report platforms withdraw public signals of loan quality in order to retain investors in a model similar to Rock (1986), in which informed institutional investors impose adverse selection costs. We note that over our longer sample horizon, we observe the opposite trend in information disclosure, which makes a withdrawal of public signals less likely.[19] However, this should only apply if funding markets are predominantly active (Figure 1 (3)), which is contrary to the evidence in Balyuk and Davydenko (2018) that institutional investors on Prosper are primarily passive (Figure 1 (2)). An alternative explanation to the withdrawal of public signals noted in Vallee and Zeng (2019) is that the MLP increases the dispersion of expected default within a credit grade, allowing the platform greater leeway to reward investors in passively allocated markets.

4.4 Exogenous Shift in Regulatory Scrutiny: San Bernardino Shooting

Sections 4.2 and 4.3 provide robust evidence that during periods of high institutional demand, institutional investors are allocated loans with higher default rates, consistent with our regulatory scrutiny hypothesis. The results also show that retail investors are allocated lower-defaulting loans during this period. It would be difficult to argue that retail investors demand better-quality loans in the same fashion that institutional investors demand loans. Retail investors are atomistic, have substantially lower investment budgets, and the fractional funding market is competitive—the platform cannot allocate a particular loan to a particular individual. Thus, any channel driving this platform behavior is likely to come from something other than retail investors.

A recent paper by Kubick et al. (2016) finds that firms that initially engage in aggressive tax avoidance engage in less tax-avoidance behavior after SEC scrutiny than their non-scrutinized peers. Similar behavior was observed for NASDAQ dealers following the *New York Times* publication of Christie and Schultz (1994) as documented by Christie et al. (1994). If FinTech platforms were also subject to intense regulatory scrutiny regarding retail-investor involvement on the platform, and if they were as a result to conservatively allocate loans when regulators are likely to monitor, then their behavior would be

[19] While Vallee and Zeng (2019) focus on the reduction in borrower/loan information on 11/7/14 from 100 to 50 descriptive variables, data downloaded from the platform currently contains more than 150 fields. These fields became increasingly availabile beginning in 2015–2016, when their sample ends.

consistent with the results of Kubick et al. (2016). This may be especially true if the cost of noncompliance is high, as during the platform closures in 2008–2009 or with class-action lawsuits filed by state security regulators.[20] In this section, we first provide context to the regulatory environment for LendingClub that suggests it was subjected to heavy regulatory scrutiny prior to our sample period. Then we test whether platform loan quality suffers during periods of high institutional loan demand. We conclude with a test utilizing an exogenous increase in regulatory scrutiny outside of loan-demand shifts to show the platform shifts loan quality during periods of elevated regulatory oversight.

When the LendingClub and Prosper lending platforms were founded during the financial crisis, they immediately encountered heavy regulatory oversight. Within their first year of operations, both platforms were in discussions with the SEC regarding their loan-origination processes, and by 2008 they were forced to cease origination activity for six to nine months while they complied with SEC requests (Cornaggia et al., 2018; Rigbi, 2013). One of the principal issues was that marketplace lending platforms allowed retail-investor involvement in the loan-funding process. Subsequent competitors that have narrowed their investor base to only institutional investors have been subjected to substantially less disclosure requirements and fewer regulatory interventions.[21] After the 2008 closures, the marketplace lending platforms were forced to comply with federal and state investor bureau oversight and were prevented from exercising Blue Sky exemptions aimed at simplifying the intermediation process. For example, platforms were forced to register their aggregate loan originations at the federal level with the SEC, to file daily updates on all standard program loans offered to investors, to register a security offering with every state that housed investors, and to reapply for security registration regularly (Cornaggia et al., 2018). The government accountability office (GAO) report on peer-to-peer lending (2011) documents multiple state-security-regulator interventions, including cease-and-desist letters and fines. Cornaggia et al.

[20] In 2008, the North American Security Administrators Association filed a class-action lawsuit against Prosper related to its unregistered issuance of fractional notes.

[21] Upstart, Avant, and Marcus are competing platforms focusing solely on institutional investment capital that have had substantially milder regulatory oversight than LendingClub and Prosper. For example, none of these lending platforms file daily regulatory updates on loans originated, nor do they have to seek state security regulator registration, because they are able to exercise a variety of exemptions.

(2018) also report that LendingClub and Prosper were the 10th and 25th most active SEC filers of all time by the end of 2017, even though both firms were only founded in 2006. Based on these monitoring and disciplinary actions, we view the platforms as being subjected to a high level of federal and state regulatory scrutiny.

We next investigate whether platforms are forced to compromise on loan quality to meet institutional investor demand. One way the platform might compromise on loan quality would be through the credit-screening process. If elevated loan demand influences the credit-screening rejection rate of the platform, this would suggest that the platform's ability to stir loan supply from borrowers is limited and that loan quality may deteriorate during periods of high loan demand from institutional investors. In Table 7 columns (1)–(3), we use a Probit model to regress the platform rejection decision on loan/borrower attributes and institutional investor loan demand. We include borrower attributes but also incorporate the aggregate loan-supply volume (rejected loan volume plus accepted loan volume) on the platform. We report the coefficient estimates of the odds ratio in columns (1)–(3) to ease interpretation. The results show in all three specifications that rejection rates are negatively correlated with the amount of institutional loan demand. The likelihood of a loan being rejected, even after controlling for borrower quality, falls as institutional loan demand increases. This suggests the platform uses the credit-screening process to adjust loan supply to match investor loan demand.

While columns (1)–(3) are consistent with deteriorating loan quality during periods of increased institutional loan demand, if the platform is demand constrained, then it is possible that the quality of rejected loans is similar to that of the loans passing the credit screen. Thus, a lowering of rejection rates, while consistent with our story, does not necessitate a deterioration in loan quality. In columns (4)–(6) of Table 7, we show that as the aggregate amount of loans demanded by institutional investors increases, loan quality indeed deteriorates. The results in column (4) suggest that default rates increase by 2.1% in aggregate for a 1% increase in the institutional loan amount. Using the raw level in column (5) yields similar results. Together, the results in Table 7 suggest that while the platform may be loan-demand constrained, its ability to stir loan supply is limited and loan quality declines during elevated institutional loan demand.

While the results in Tables 4–7 are consistent with a regulatory scrutiny channel, we are forced to infer the relationship between loan demand and regulatory monitoring in the earlier tests. To provide additional evidence of this regulatory scrutiny channel, we examine platform allocation behavior around an exogenous shock to regulatory monitoring. In early December 2015, a mass shooting was reported in San Bernardino, CA. The shooter obtained funding from a loan originated on a competing platform, Prosper Marketplace, and the media released details of the connection on 12/8/15. While Prosper received much attention as a result, the bank that underwrites loans for both Prosper and LendingClub came under investigation from the FBI, received increased scrutiny from state legislators, and was investigated by the consumer financial protection bureau (CFPB).[22] During this period, both platforms also experienced a temporary wave of increased regulatory oversight. Importantly though, loan demand on the LendingClub platform was not materially changed by the news release.

In Table 8, we limit the sample to the period around the December 8, 2015, press release and include an indicator equal to one following this event. Using the 120 days before and after the press release, we show that afterward, retail investors are allocated substantially lower defaulting loans. In column (1), the hazard ratio for the post-event period indicates that retail investor default rates decrease by 14.9% while institutional loan default rates increase by 11.7%. We include indicators of high institutional loan demand in column (2), and the post-event indicator remains less than one and significant. Column (3) adds indicators for the triple interaction, although neither is statistically significant. Interestingly, in the period after the event, retail investors are allocated loans with lower default rates than institutional investors. Retail (institutional) investors are allocated loans with default rates 12.5% (10.7%) lower than the base hazard during periods of low institutional loan demand; during periods of high institutional loan demand, the same

[22] See Internet Appendix Table A2 for a list of media citations covering the relation between Prosper and the shooting and the wave of regulatory scrutiny following the incident. Technically, the underwriting process for both marketplace lending platforms involves an industry bank to underwrite the loan—in this case, WebBank. Platforms purchase the loan in 1–3 days following origination and issue a separate security to investors. The cash flows of the separate security (note) are tied to the payments of the borrower, and the platform is removed from any credit risk of the borrower. Importantly, it was the industry bank common to both platforms that fell under heavy regulatory monitoring during the period, influencing the underwriting of LendingClub.

allocations are 20.4% (9.7%) lower. This suggests that following the increase in regulatory monitoring, the platform shifted loan allocation to favor retail investors regardless of loan demand.

We conduct a series of robustness tests around this result. First, in Table 8 we replace the *Post* indicator with a series of 15-day indicators through the sample. We graph the interaction of *Whole Loan* with each of these indicators along with their 95% confidence intervals in Figure 4. As shown in the figure, the platform appears to shift loan allocation approximately 50 days following the press release. This corresponds with the period when the state of California launched a broad inquiry into marketplace lending firms. The figure also shows that in the 15-day period 90–105 days before the press release, loan hazard rates on the platform were substantially lower for institutional investors. To ensure the event study results are not spuriously driven by this period, we omit the 15 days included in this window, and in unreported results, we verify that the hazard rates are qualitatively similar and of similar statistical significance.

5. Additional Robustness Tests

5.1 Asset-Backed Security (ABS) Issues

One of the forces driving the growth of institutional loan demand is the ability of institutional investors to purchase and pool loans from the platforms to originate asset-backed securities (ABS). Figure 5 shows the volume of loans originated each month for both Prosper and LendingClub that were sold to ABS issuers. In Table 4, we examine periods of high institutional investor loan demand. It is possible these periods correspond with ABS purchasing activity, which could influence the interpretation of the results if ABS issuers exhibit different purchasing behavior than buy-and-hold investors such as commercial banks.[23]

To disentangle ABS purchasing activity from other periods of high institutional investor loan demand, we first examine the three ABS issues backed by LendingClub loans during our sample period. Table 9 Panel A shows the FICO score composition of the loans underpinning each ABS. As the table

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[23] LendingClub reports aggregate investor statistics in their 10-k from 2017 onwards. Banks appear as the largest investor type, funding 36–44% of loans in 2017. See "Investments by Investment Channel and Investor Concentration" in 10-k https://www.sec.gov/Archives/edgar/data/1409970/000140997018000231/a201710-k.htm.

shows, early ABS issues were weighted heavily toward the bottom portion of the FICO distribution (that passed the credit screen on the platform). Also noteworthy is that the first ABS issue, ARCT 2017-1 from Arcadia, is the only ABS issued by a third party; the other two ABS issuances, CLUB 2017-P1 and CLUB 2017-P2, were issued by LendingClub itself. We mimic the structure of Table 4, substituting *High W Fraction* for an indicator that identifies the period when loans were likely purchased for the ABS (*ABS Activity*). We then split the loan sample by borrower FICO score buckets identified in Table 9 Panel A. The results reported in Table 9 Panel B suggest a familiar pattern of preferential allocation for institutional investors during the non-ABS periods, and during periods of ABS-loan purchasing activity, the reverse, where allocation favors retail investors at the expense of institutional investors. It also shows that the loans most affected by the ABS activity are the FICO grades most likely to be included in the ABS.

To disentangle ABS purchasing activity from non-ABS high loan demand, we include both the *ABS Activity* and *High W Fraction* indicators in the same specification. Because there is some overlap between *High W Fraction* and *ABS Activity*, we orthogonalize the two indicators such that any overlap is included in the *ABS Activity* measure. Table 10 repeats the test from Table 4 with an additional indicator for ABS activity days. The results in column (1) and (2) suggest that both ABS activity loan demand and non-ABS loan demand induce the platform to allocate lower-defaulting loans to retail investors. The swing in allocation appears to be more drastic for ABS activity days. Splitting up the different ABS issues in columns (3)–(4) reveals that the platform allocation behavior is not dependent on the ABS issuer. This would imply newly implemented credit-risk retention rules imbued as part of the Dodd-Frank Act do not appear to shift platform behavior. We find this interesting: the entities issuing marketplace lending ABS have shifted dramatically from third-party ABS issuers pre-Dodd-Frank to platform-issued ABS following its implementation. We find similar results in the next section, where we report the test using loan data for the Prosper platform. This is significant because the Prosper platform was more heavily utilized by ABS-issuing institutions than LendingClub.

5.2 Generalizability to Other Marketplace Lending Platforms (Prosper)

In the current analysis, we have focused exclusively on one marketplace lending platform because of multiple econometric features that make it favorable for testing. However, it is important to verify the generalizability of our results to other FinTech credit market platforms. To give some measure of confidence, in this section we repeat key tests throughout this paper for the Prosper platform.[24] Importantly, Prosper underwent similar regulatory scrutiny in 2006–2009 and has maintained retail investor inclusion. In Table 11 we show that the regulatory scrutiny channel also appears to influence the Prosper platform's behavior. Columns (1)–(3) show a similar fair allocation on average for the sample. Column (4) shows that for Prosper, increased loan demand from institutional investors does not evoke preferential treatment for retail investors. However, columns (5)–(6) show that when institutions are being allocated loans for ABS activity, retail investors are allocated loans with lower default rates and institutional investor default rates increase. Notably, for the Prosper platform the fraction of institutional investment driven by ABS activity is substantially higher (see Figure 5), with almost 50% of origination capital flowing from ABS investors in 2015. This may explain why on the Prosper platform, ABS issuing activity appears to trump the high loan demand indicator. Critically, though, we observe a similar allocation choice to protect retail investors during times of increased loan demand from ABS loan-purchasing activity.

5.3 Reallocation of Loans

As we identify in Figure 1, loans initially placed in the active institutional investor pool can be reallocated to retail investors if they are not funded by active institutional investors. It is possible these reallocated loans represent a winner's curse (Rock, 1986) for retail investors. Alternatively, it is possible these reallocated loans may have superior performance relative to the average loan assigned to retail investors if they are reallocated during periods of low institutional investor loan demand. We examine the

[24] Details on sample construction are relegated to internet appendix section IA1.2.

performance of reallocated loans in Table 12. In column (1) we first look at the average performance of reallocated loans. It appears that on average the loans selected by institutional investors and those reallocated to retail investors from the institutional market are statistically no different than the loans initially allocated to and funded by the retail market. However, when we examine periods of high institutional investor loan demand, we see results consistent with the earlier tables. Column (2) suggests that during periods of low institutional investor demand, both loans allocated and funded by institutional investors (*Whole Funded*) and loans reallocated to retail investors (*Reallocated*) have lower default rates than loans initially allocated to retail investors. Similar to Table 4, when institutional investor loan demand is high, we observe retail investors being allocated lower-defaulting loans and institutional investors being allocated loans with higher default rates. During periods of high institutional investor loan demand, the reallocated loans appear to represent a winner's curse (Rock, 1986), but during periods of low institutional investor demand, the reallocated loans appear to have an even lower default rate than those funded by institutional investors.

Since reallocated loans are only reallocated from the active funding market, and since the model in Rock (1986) suggests the platform may have to allocate especially low-defaulting loans in such a competitive market to overcome a within (institutional) market winner's curse, it is possible the *Reallocated* hazard rate represents the enhanced allocation in such a market. The *Whole Funded* hazard rate, on the other hand, is a mix of passively allocated loans and actively funded loans. Yet when the institutional loan demand is high and active institutional investors can choose not to fund loans, the lemon loans appear to be especially sour. In columns (3) and (4) we limit the sample to loans originated prior to May 2016. Following an organizational shift in May 2016, the platform dramatically reduced the practice of reallocation. Focusing on the period when reallocation rates ranged from 3.7% to 27.6% of loans allocated to the institutional investors, we find that the reallocated loans consistently default more than the institutionally funded loans. This implies that the lower default rate in columns (1)–(2) could be driven by the few outliers allowed to be reallocated since May 2016.

6. Conclusion

We investigate the assertion that marketplace lending platforms fairly allocate newly originated loans between institutional and retail markets. In the first portion of the paper, we show that platforms fairly allocate loans on average over our sample. Loans allocated to institutional investors and retail investors appear to have statistically indistinguishable default rates on average. However, when we incorporate institutional investor's increase in demand for loans, we obtain evidence consistent with both the *quid pro quo* and regulatory scrutiny channels. The results show that institutional investors are allocated loans with lower default rates during periods of low institutional loan demand, consistent with a *quid pro quo* relationship between institutional investors and the platform. Conservatively, we estimate that institutional investors are allocated loans with 8.4% lower default rates during such periods. Using the sample average default and interest rates, this should roughly translate to a 27 BP difference in net return between the two groups. When institutional loan demand increases, loan allocation deteriorates for institutional investors and default rates increase by 5.8%. We show that in conjunction with this decline, retail investors are offered loans with a 12.8% lower default rate. The decline in loan quality for institutional investors during high institutional loan demand is consistent with our proposed regulatory scrutiny channel. If regulators are more inclined to monitor when markets "heat up," a platform anticipating monitoring may reduce *quid pro quo* behavior toward institutional investors.

To understand why MLP might allocate loans with lower default rates to retail investors during periods of elevated regulatory monitoring, we discuss the heavy regulatory pressure felt by FinTech platforms in their infancy. We argue that MLP were subjected to heavy state and federal regulatory scrutiny early in their firm life cycle. This included additional monitoring, enforcement actions, and the temporary closure of both major U.S. FinTech credit platforms studied here. Given the high cost of noncompliance, an MLP may swing allocation behavior in favor of retail investors during periods likely to engender regulatory monitoring. Consistent with this notion, we show that high-demand periods coincide with a lowering of rejection rates in the loan-screening process and an aggregate increase in default rates. Thus, the reactionary behavior would be similar to what Kubick et al. (2016) show for firms engaging in tax-avoidance behavior after some type of regulatory intervention. Finally, we also show that following an exogenous increase in regulatory scrutiny (the San Bernardino shooting), the marketplace lending platform under examination shifted its allocation preference from institutional investors to retail investors, regardless of loan demand. One of our main contributions is to demonstrate the extent to which heightened regulatory oversight can alter platform behavior in the growing FinTech area.

We focus on the FinTech platform LendingClub, yet we show that the main results are also present on a competing U.S. platform (Prosper). While the majority of other U.S. competitors in FinTech credit markets have shifted away from retail investment, 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) and initial coin offerings via DAOs. Currently, both mix retail and institutional investors in much the same way marketplace lending platforms did prior to our sample period. However, as markets expand and draw additional institutional investor participation, it is possible these alternative platforms will also segregate investors and make allocation decisions like those the MLPs made. Our results suggest incentives among FinTech platforms matter and that future study of emerging FinTech entities is likely warranted. Given the global growth in size and scope of the marketplace lending platforms and the wide use of technology in other areas of capital intermediation, such as crowdfunding and initial coin offerings, our results suggest the need for a more careful understanding of platform behavior. 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.

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Appendix: Variable Definitions

Variable	Definition
Default	An indicator equal to one when a loan is reported as defaulted, charged off, or delinquent by more than 30 days. (i.e., Loans with loan status of Default, Charged Off, or Late by 31-120 days).
Prepayment	An indicator equal to one when a loan is fully paid including loans settled before the maturity date. (i.e., Loans with loan status of Fully Paid).
Whole Loan	An indicator equal to one when a loan is initially assigned to the whole loan market.
Whole Funded	An indicator equal to one when a loan is initially assigned to the whole loan market and funded in the whole loan market.
Reallocated	An indicator equal to one when a loan is initially assigned to the whole loan market but reallocated to the fractional market where it is funded
Post	An indicator equal to one in the 120 days following the San Bernardino shooting press release on 12/8/15 which claimed the shooter obtained funding from Prosper.
Borrower Credit Information	
DTI	The borrower's debt to income ratio (%).
Inq6Month	Number of credit inquiries on borrower's credit report in the six months before listing.
YrsFirstCredit	Borrower's credit history length, i.e. the number of years between borrower's first credit line and the time of listing.
Utilization	The percentage of credit lines that the borrower has used at the time of listing.
$Utilization^2$	The quadratic term of Utilization multiplied by 0.01.
Employment	A series of dummy variables that indicate the length of employment of the borrower. LendingClub groups the length of employment into 12 categories as follows; (1) < 1 Year, (2) 1 year, (3) 2 years, (4) 3 years, (5) 4 years, (6) 5 years, (7) 6 years, (8) 7 years, (9) 8 years, (10) 9 years, (11) 10+ years, and (12) n/a.
Credit Score Range	The credit score reported in the LendingClub rejected loan file is the VantageScore 2.0 which ranges from 501-990. In the sample of loans that pass the credit screen, the platform reports the FICO credit score which ranges from 300-850 similar to VantageScore's 3.0. We follow VantageScore's table for converting VantageScore 2.0 to VantageScore 3.0, by linearly compressing scores in three regions: < 571, between 571 and 930, and >930. See https://your.vantagescore.com/interpret_scores for more information.
Loan Information	
Amount Requested	The natural log of the loan amount in US dollars requested by the borrower.
5YearTerm	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.
Interest Rate	The stated interest rate, i.e., the rate the investor should receive on their investment, which is approximate to the coupon rate minus any service charge.
Interest $Rate^2$	The quadratic term of Interest Rate
CreditGrade	An indicator equal to one for each credit grade assigned by the platform: LendingClub (A, B, C, D, E, F, G).

Loan Purpose	A series of dummy variables indicating purpose of borrowing. For LendingClub the purpose of borrowing includes: (1) Debt Consolidation, (2) Credit Card, (3) Home Improvement, (4) Medical/Moving/Vacation/Wedding/Major Purchase, (5) Small Business, (6) Education, (7) Renewable Energy and Other.
Platform Characteristics	
Total Supply	The log of weekly aggregate dollar volume of loan applications (both rejected and accepted) on the platform.
High W Fraction	An indicator equal to one if the dollar fraction of loans initially assigned to the whole loan market is larger than the sample median.
High W Fraction MA30	An indicator that equal to one if the 30-day moving average of the daily dollar fraction of loans initially assigned to the whole loan market is larger than the sample median.
High W Fraction50	An indicator equal to one if the dollar fraction of loans initially assigned to the whole loan market is larger than 50%.
High W Fraction50 MA30	An indicator that equal to one if the 30-day moving average of the daily dollar fraction of loans initially assigned to the whole loan market is larger than 50%.
High W Fraction*	An indicator equal to *High W Fraction* when *ABS Activity* is zero. When *High W Fraction* and *ABS Activity* are both one, we set *High W Fraction** equal to zero.
High W Fraction MA30*	An indicator equal to *High W Fraction MA30* when *ABS Activity* is zero. When *High W Fraction MA30* and *ABS Activity* are both one, we set *High W Fraction MA30** equal to zero.
W Amount	The daily dollar amount initially assigned to the whole loan market.
High W Amount	An indicator equal to one if the daily dollar amount initially assigned to the whole loan market is larger than the sample median
High W Amount MA30	An indicator that equal to one if the 30-day moving average of the daily dollar amount initially assigned to the whole loan market is larger than the sample median
ABS Activity	An indicator for the ±30-day window around the average implied origination date. Identifies the period of time with institutional investors are most likely to be funding loans for ABS issue. Average implied origination date is inferred from the statistical cutoff date and the average age of loans in the ABS on that date.
ABS Internal Period	An indicator equal to one if *ABS Activity* equals one and the ABS is issued by Lending Club.

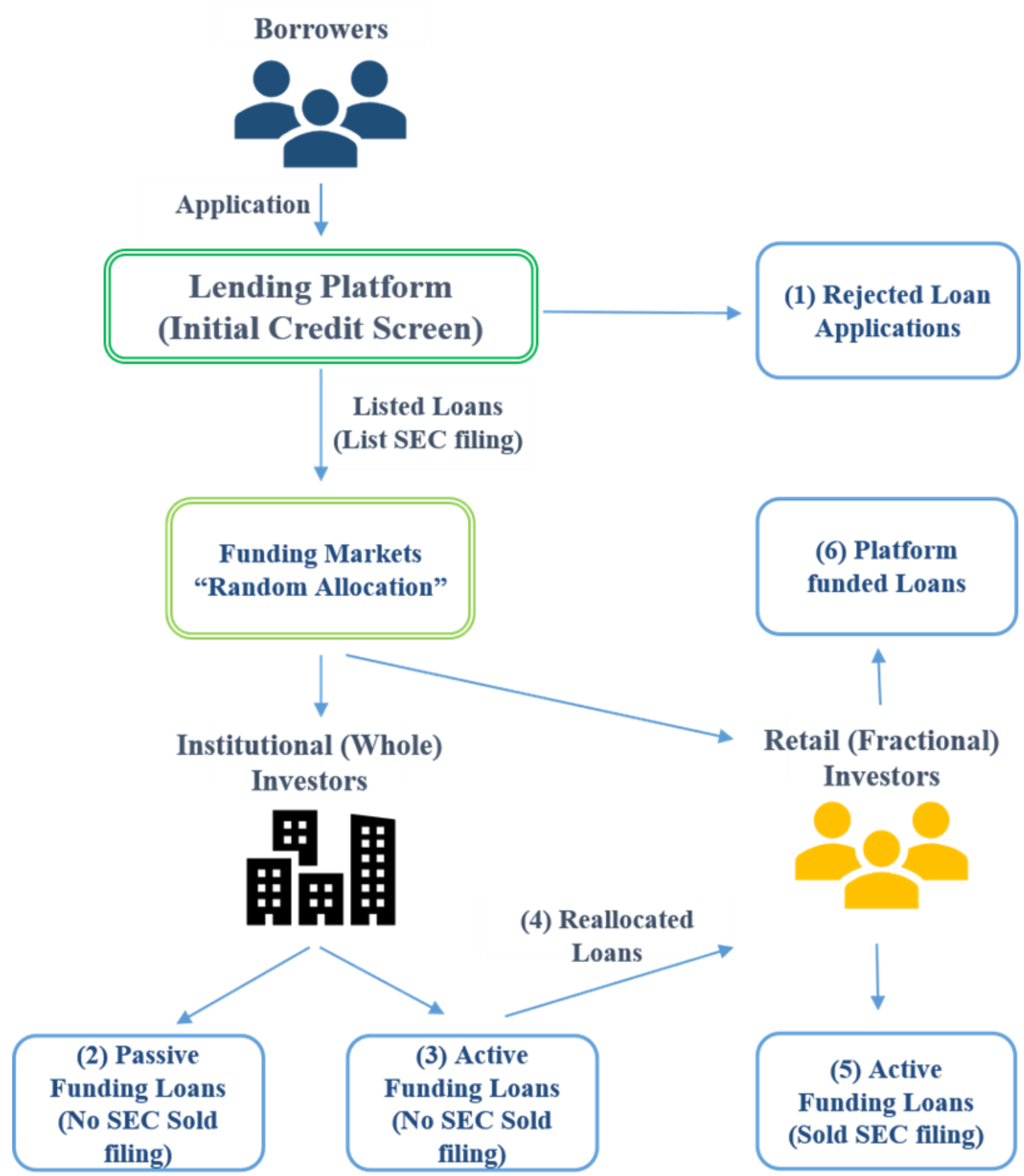

Figure 1. Loan Allocation Process for Marketplace Lending Platforms

In this figure, we show the loan allocation process. After borrowers submit a loan application, the platform performs a credit screen, (1) rejecting the majority of loan applications. Once a loan application passes the initial screen, loans are allocated to one of two funding markets: institutional (whole loan) or retail (fractional loan). Loans allocated to institutions are further selected for passive funding (2) or active funding (3) by the platform. Passively funded loans are packaged in groups and sold to institutional investors or used to back passive-investment funds offered to investors. In the active funding markets (3 and 5), investors compete to fund the loans. Loans not funded in the active institutional market are reallocated to be funded (4) in the retail market. Loans not funded in the retail market are funded by the platform (6).

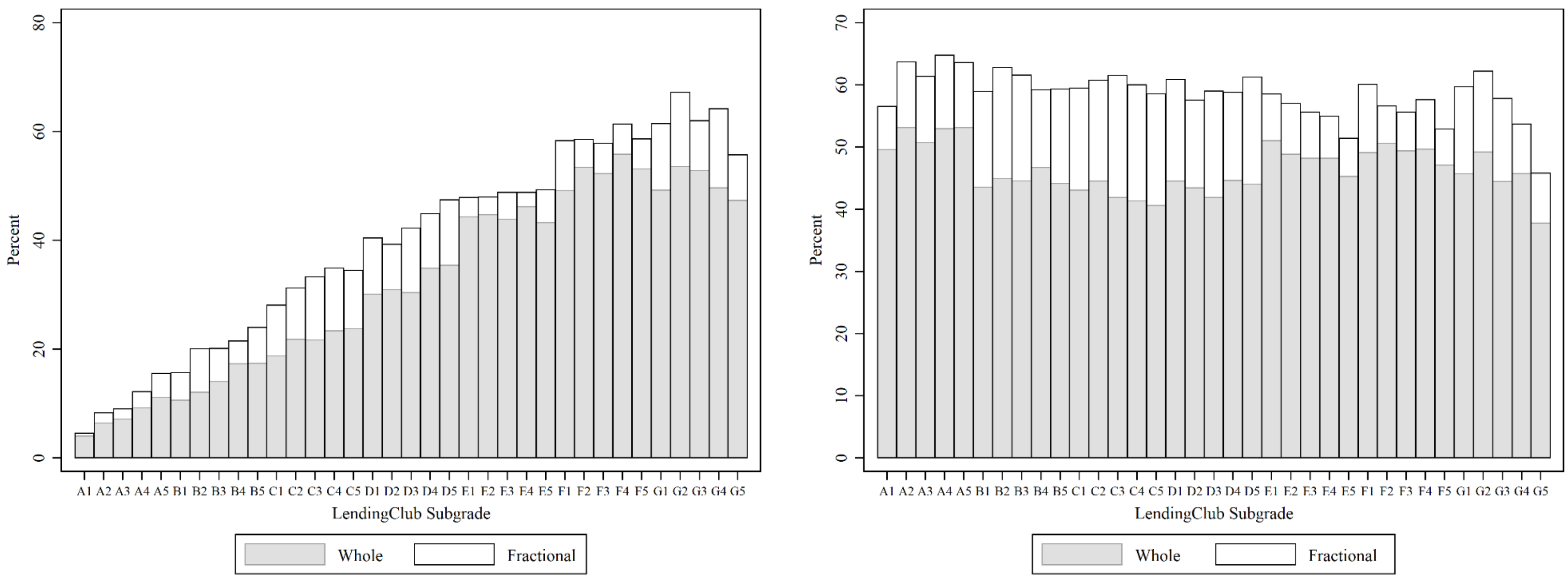

Figure 2. Default and Prepayment Rate for LendingClub by Funding Market and Credit Grade

The figure on the left shows the average default rate, and the figure on the right shows the average prepayment rate over our sample period (9/14–12/17) for LendingClub Standard Program loans by credit subgrade and funding market. Institutional investors fund loans in the whole loan market while retail investors fund fractional loans.

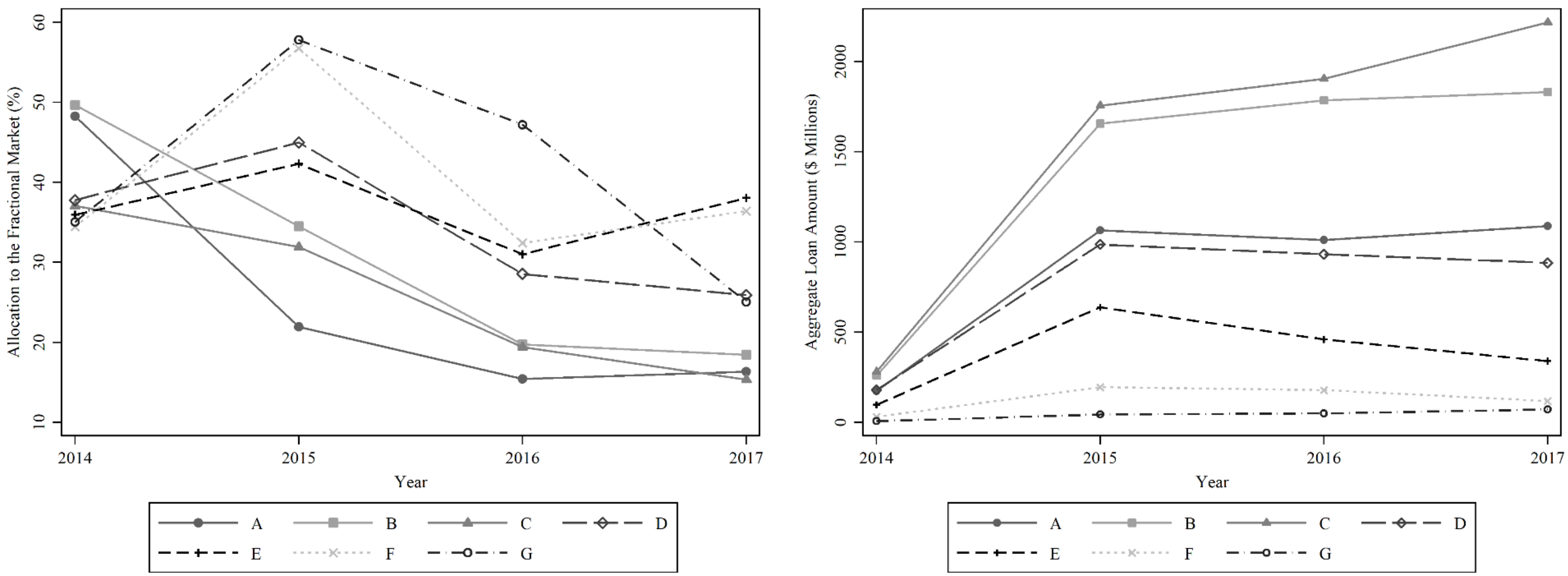

Figure 3. Dollar Fraction of Loans Allocated to the Retail Market and Annual Loan Origination by Loan Credit Rating

Marketplace lending platform loans are allocated to either the institutional funding market or the retail funding market. The chart on the left reports the dollar fraction of loans assigned to the retail loan market by credit rating each year for LendingClub. The chart on the right shows the aggregate loan origination volume by credit grade each year.

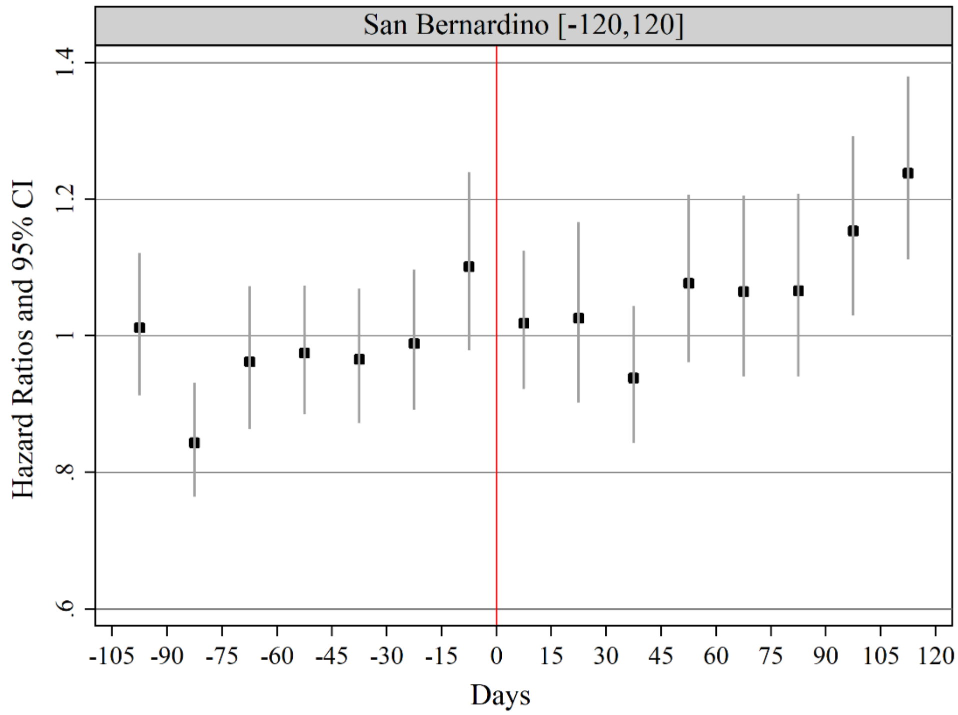

Figure 4. Institutional Default Hazard Ratios around San Bernardino-Prosper Press Release

This figure reports the hazard ratios for the loans allocated to institutional investors in the ±120 days around the press release linking marketplace lending platforms to the San Bernardino shooting event. We split the *Post* indicator in Table 7 into 15-day intervals, and figure reports the hazard ratio of the interaction of these indicators with the *Whole* allocation indicator. The assailant in the shooting event obtained funding through a competing marketplace lending platform. After the press release, marketplace lending platforms experienced additional regulatory scrutiny. Table A2 in the appendix documents media coverage of the event and the subsequent regulatory actions resulting from the event.

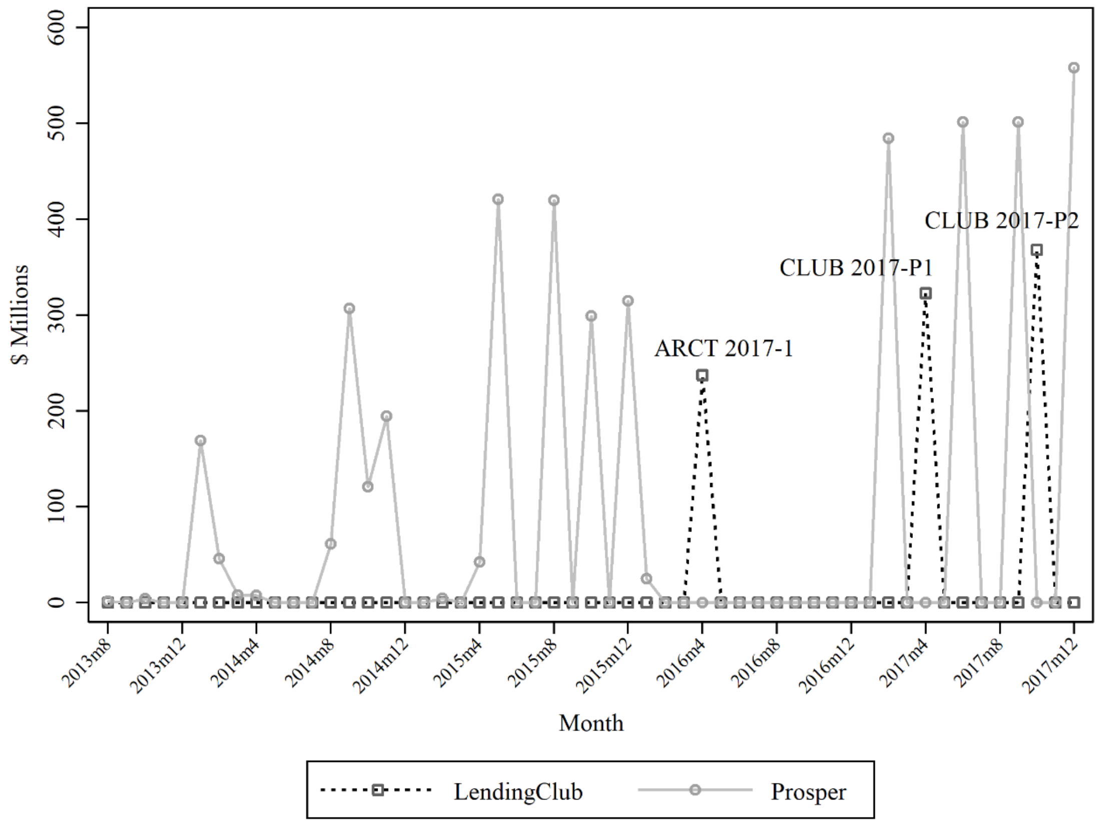

Figure 5: Monthly Securitization Volume per Marketplace Lending Platform

This figure reports the approximate volume of loans ($ millions) funded each month by asset-backed security (ABS) issuers on LendingClub and Prosper. Marketplace lending platforms allow ABS issuers to fund a predetermined amount of loans that the ABS issuer subsequently pools to create ABS. We back out the average implied origination date of loans in each ABS issue from the statistical cutoff date and average loan age. Using this, we assume loan origination activity occurs within a 30-day window around the average implied origination date.

Table 1. Summary Statistics by Credit Category and Initial Market Allocation

Summary statistics of our main variables for LendingClub. Panel A presents statistics for the sample, including current and defaulting loans. After a loan application is received by the platform, it is initially allocated to either the retail (Fractional) funding market or the institutional (Whole) funding market. Loan outcomes by funding market and credit category are presented in Panel B.

Panel A. Default Sample

Variable Name	Mean	Std. Dev.	Q1	Median	Q3
Interest Rate	13.50	4.935	9.930	12.74	16.020
Interest Rate^2	205.4	157.6	98.61	162.3	256.6
DTI	19.84	45.97	12.74	18.84	25.60
Amount Requested	9.434	0.702	8.987	9.547	9.923
Utilization	51.87	24.25	33.60	51.90	70.50
Utilization^2	3,278	2,582	1,129	2,694	4,970
Inq6Month	0.537	0.835	0.000	0.000	1.000
YrsFirstCredit	16.70	7.829	11.00	15.00	21.00
5YearTerm	0.354	0.478	0	0	1
Credit Grade A	0.145	0.352	0	0	0
Credit Grade B	0.286	0.452	0	0	1
Credit Grade C	0.320	0.466	0	0	1
Credit Grade D	0.148	0.356	0	0	0
Credit Grade E	0.070	0.255	0	0	0
Credit Grade F	0.023	0.150	0	0	0
Credit Grade G	0.008	0.086	0	0	0
Employment: < 1 year	0.087	0.283	0	0	0
Employment: 1 year	0.066	0.248	0	0	0
Employment: 2 years	0.090	0.286	0	0	0
Employment: 3 years	0.079	0.270	0	0	0
Employment: 4 years	0.060	0.237	0	0	0
Employment: 5 years	0.060	0.237	0	0	0
Employment: 6 years	0.042	0.201	0	0	0
Employment: 7 years	0.037	0.188	0	0	0
Employment: 8 years	0.039	0.193	0	0	0
Employment: 9 years	0.037	0.188	0	0	0
Employment: 10+ yrs.	0.335	0.472	0	0	1
Employment: n/a	0.070	0.255	0	0	0
Debt Consolidation	0.572	0.495	0	1	1
Credit Card	0.217	0.412	0	0	0
Home Improvement	0.074	0.262	0	0	0
Major Purchase	0.050	0.218	0	0	0
Small Business	0.011	0.106	0	0	0
Education	0.010	0.100	0	0	0
Other	0.065	0.247	0	0	0
N	774,214				

Panel B. Loans with Loan Status by Initial Allocation

Loan Grade: Full				
Initial Allocation	Current	Default	Prepaid	Default Sample (Default+Current)
Whole	462,422	120,671	388,123	583,093
Fractional	129,332	61,789	193,478	191,121
Total	591,754	182,460	581,601	774,214

Table 2. Summary Statistics by and Initial Market Allocation and Credit Grade

This table reports the sample mean of our main variables for LendingClub grouped by market assignment and credit grade. 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). Then it is initially allocated to either the retail (Fractional) funding market or the institutional (Whole) funding market.

Panel A. Fractional (Retail)

Variable	A	B	C	D	E	F	G
Average FICO score	726.0	695.5	687.3	684.4	683.5	683.2	681.3
Default (%)	4.18	9.26	15.91	22.89	29.17	37.90	41.50
Prepayment (%)	59.50	54.73	50.54	45.83	39.79	35.54	33.57
Current (%)	36.31	36.01	33.54	31.28	31.05	26.56	24.94
Interest Rate (%)	7.017	10.33	13.68	17.56	21.48	25.61	28.54
Interest Rate^2	50.13	108.0	188.2	310.4	468.1	663.7	818.2
DTI (%)	16.18	17.93	19.86	21.38	22.01	22.82	22.69
Amount Requested	9.354	9.240	9.22	9.310	9.450	9.646	9.722
Utilization (%)	39.69	51.11	55.22	56.59	56.82	56.26	55.57
Utilization^2	2,105	3,162	3,605	3,770	3,812	3,777	3,695
Inq6Month	0.312	0.463	0.644	0.797	0.913	1.037	1.186
YrsFirstCredit	18.52	16.88	15.61	15.26	15.06	14.81	14.35
5YearTerm	0.023	0.073	0.115	0.197	0.384	0.656	0.709
Employment: < 1 year	0.080	0.081	0.087	0.085	0.086	0.079	0.075
Employment: 1 year	0.059	0.065	0.071	0.070	0.068	0.064	0.071
Employment: 2 years	0.086	0.091	0.096	0.092	0.095	0.092	0.091
Employment: 3 years	0.079	0.080	0.083	0.082	0.083	0.084	0.079
Employment: 4 years	0.059	0.061	0.061	0.063	0.063	0.063	0.065
Employment: 5 years	0.059	0.060	0.060	0.061	0.058	0.060	0.058
Employment: 6 years	0.042	0.042	0.042	0.042	0.044	0.042	0.050
Employment: 7 years	0.039	0.040	0.040	0.040	0.039	0.039	0.043
Employment: 8 years	0.044	0.044	0.043	0.042	0.042	0.049	0.040
Employment: 9 years	0.039	0.038	0.037	0.036	0.036	0.039	0.036
Employment: 10+ yrs.	0.355	0.332	0.310	0.307	0.311	0.323	0.330
Employment: n/a	0.059	0.066	0.070	0.079	0.075	0.066	0.061
Debt Consolidation	0.493	0.556	0.598	0.622	0.636	0.645	0.617
Credit Card	0.324	0.264	0.181	0.131	0.103	0.079	0.065
Home Improvement	0.085	0.067	0.065	0.066	0.073	0.083	0.096
Major Purchase	0.045	0.045	0.056	0.061	0.055	0.056	0.050
Small Business	0.004	0.006	0.011	0.018	0.026	0.035	0.048
Education	0.013	0.011	0.010	0.009	0.008	0.007	0.006
Other	0.037	0.052	0.079	0.093	0.099	0.095	0.119
N	46,498	108,794	106,764	70,851	36,169	11,978	3,545

Panel B. Whole (Institutional)

Variable	A	B	C	D	E	F	G
Average FICO score	728.7	700.3	691.4	686.4	685.6	683.6	682.6
Default (%)	3.92	8.54	13.86	20.95	29.17	35.66	35.93
Prepayment (%)	49.92	40.95	36.48	34.55	34.37	31.73	28.86
Current (%)	46.15	50.51	49.66	44.50	36.45	32.61	35.21
Interest Rate (%)	6.938	10.31	13.85	17.95	21.55	26.01	29.38
Interest Rate^2	49.07	107.5	193.1	324.5	471.3	684.2	867.0
DTI (%)	16.39	18.14	19.80	21.53	22.42	23.13	25.68
Amount Requested	9.372	9.345	9.442	9.545	9.745	9.811	9.852
Utilization (%)	38.21	49.30	54.38	56.92	58.02	57.86	56.40
Utilization^2	1,977	2,993	3,515	3,803	3,934	3,927	3,764
Inq6Month	0.314	0.447	0.571	0.704	0.790	0.937	1.026
YrsFirstCredit	18.57	17.15	16.27	15.73	15.65	15.20	14.76
5YearTerm	0.049	0.224	0.431	0.552	0.829	0.903	0.891
Employment: < 1 year	0.081	0.085	0.088	0.085	0.082	0.082	0.087
Employment: 1 year	0.060	0.065	0.067	0.068	0.066	0.067	0.068
Employment: 2 years	0.087	0.090	0.091	0.090	0.089	0.091	0.096
Employment: 3 years	0.076	0.079	0.080	0.079	0.079	0.080	0.086
Employment: 4 years	0.057	0.058	0.060	0.060	0.060	0.058	0.057
Employment: 5 years	0.058	0.059	0.060	0.060	0.062	0.062	0.065
Employment: 6 years	0.042	0.042	0.042	0.042	0.042	0.045	0.047
Employment: 7 years	0.038	0.037	0.038	0.038	0.038	0.040	0.040
Employment: 8 years	0.042	0.040	0.040	0.041	0.047	0.044	0.043
Employment: 9 years	0.038	0.037	0.038	0.038	0.040	0.039	0.038
Employment: 10+ yrs.	0.360	0.344	0.336	0.334	0.342	0.339	0.321
Employment: n/a	0.060	0.063	0.061	0.064	0.054	0.053	0.052
Debt Consolidation	0.480	0.545	0.601	0.640	0.683	0.696	0.675
Credit Card	0.315	0.262	0.196	0.151	0.123	0.096	0.068
Home Improvement	0.093	0.075	0.070	0.067	0.069	0.072	0.079
Major Purchase	0.047	0.046	0.049	0.048	0.041	0.042	0.041
Small Business	0.006	0.007	0.010	0.014	0.017	0.020	0.035
Education	0.014	0.011	0.009	0.008	0.007	0.006	0.006
Other	0.045	0.053	0.064	0.072	0.061	0.069	0.095
N	187,099	291,336	306,709	116,928	49,487	14,764	4,893

Table 3. Hazard Models of Loan Default Based on Initial Market Assignment

This table reports default hazard ratios, i.e. the exponential form of the coefficients for loans originated on LendingClub during the period 9/21/2014–12/31/2017. 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. Our variable of interest is *Whole Loan* which is an indicator for loans that are initially assigned to be funded in the institutional (whole loan) market. We estimate a Cox proportional hazard model for default in column (1), and in columns (2) and (3) estimate Exponential/Weibull duration models respectively. All the models contain indicators for credit grade, employment length, and loan purpose. The models also contain quarter-year fixed effects based on the date of origination. The *z*-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Model	Cox	Exponential	Weibull
	(1)	(2)	(3)
Whole Loan	0.9913	0.9906*	0.9875**
	(-1.636)	(-1.772)	(-2.364)
Interest Rate	1.159***	1.156***	1.165***
	(-25.96)	(-25.50)	(-26.74)
Interest Rate^2	1.000	1.000	0.9999
	(-0.1346)	(-0.0267)	(-0.3934)
DTI	1.00008***	1.00008***	1.00009***
	(-2.750)	(-2.600)	(-2.835)
Amount Requested	1.116***	1.111***	1.118***
	(-27.18)	(-25.87)	(-27.54)
Utilization	0.9936***	0.994***	0.9936***
	(-15.79)	(-14.75)	(-15.75)
Utilization^2	1.00002***	1.00002***	1.00002***
	(-4.948)	(-4.293)	(-4.52)
Inq6Month	1.094***	1.09***	1.097***
	(-36.11)	(-34.72)	(-37.21)
YrsFirstCredit	0.9931***	0.9933***	0.9928***
	(-20.78)	(-20.19)	(-21.52)
5YearTerm	0.3905***	0.4032***	0.3606***
	(-146.1)	(-143.3)	(-157.3)
Credit Grade FE	Yes	Yes	Yes
Employment Length FE	Yes	Yes	Yes
Loan Purpose FE	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes
Obs.	774,214	774,214	774,214

Table 4. Preferential Allocation and High Institutional Demand

This table reports default hazard ratios for loans originated on LendingClub during the period 9/21/2014–12/31/2017. 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. Our variable of interest is *Whole Loan* which is an indicator for loans that are initially assigned to be funded in the institutional (whole loan) market. *High W Fraction* (*High W Fraction50*) is equal to one if the dollar fraction of loans initially assigned to institutional investors is larger than the sample median (50%). *High W Fraction MA30* (*High W Fraction50 MA30*) is equal to one if the 30-day moving average of the dollar fraction of loans initially assigned to institutional investors is larger than the sample median (50%). *High W Amount is* equal to one if the dollar amount of loans initially assigned to institutional investors is larger than the sample median. *High W Amount MA30* is equal to one if the 30-day moving average of the dollar amount of loans initially assigned to institutional investors is larger than the sample median. All the models contain the same set of loan/borrower characteristics in Table 3 and include indicators for credit grade, employment length, 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.

Model	Cox						Exponential	Weibull
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Whole Loan	0.9164***	0.8871***	0.8334***	0.7921***	0.9333***	0.9178***	0.9179***	0.9014***
	(-12.71)	(-17.45)	(-10.34)	(-12.52)	(-9.008)	(-12.20)	(-12.476)	(-15.121)
High W Fraction	0.8722***						0.8745***	0.8546***
	(-14.51)						(-14.251)	(-16.696)
Whole Loan × High W Fraction	1.213***						1.2067***	1.2504***
	(-18.50)						(18.01)	(21.410)
High W Fraction MA30		0.8024***						
		(-21.03)						
Whole Loan × High W Fraction MA30		1.302***						
		(-25.61)						
High W Fraction50			0.9132***					
			(-8.114)					
Whole Loan × High W Fraction50			1.213***					
			(-10.52)					
High W Fraction50 MA30				0.8748***				
				(-8.537)				
Whole Loan × High W Fraction50 MA30				1.274***				
				(-12.57)				

Table 4. Preferential Allocation and High Institutional Demand (Continued)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
High W Amount					0.9321***			
					(-8.075)			
Whole Loan × High W Amount					1.118***			
					(-10.97)			
High W Amount MA30						0.8579***		
						(-15.79)		
Whole Loan × High W Amount MA30						1.19***		
						(-17.10)		
Loan/Borrower Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Credit Grade FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan Purpose FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	774,214	774,214	774,214	774,214	774,214	774,214	774,214	774,214

Table 5. Hazard Models of Loan Default with Adjustment for Sample Selection

This table reports hazard ratios, i.e. the exponential form of the coefficients for a two-step default hazard similar to Heckman (1979) for linear models. We present the second stage hazard model in Panel A and the first stage Probit model of selection in Panel B. From the first stage, we calculate the *Inverse Fisher's Z* (similar to an inverse mills ratio for linear models) which is included in the second stage exponential hazard model. Our variable of interest is *Whole Loan* which is an indicator for loans that are initially assigned to be funded in the institutional (whole loan) market. *High W Fraction (High W Fraction*50) is equal to one if the dollar fraction of loans initially assigned to institutional investors is larger than the sample median (50%). The sample is composed of rejected loan applications and loans that pass the credit screen. The second stage of the models includes indicators for credit rating, length of employment, loan purpose, and year-quarters. The *z*-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A. Second Stage Exponential Hazard

	Default			
	(1)	(2)	(3)	(4)
Whole Loan	0.9544***	0.9537***	0.8850***	0.8850***
	(-32.14)	(-31.70)	(-23.12)	(-22.58)
High W Fraction	0.9541***	0.9534***		
	(-30.87)	(-30.33)		
Whole Loan × High W Fraction	1.074***	1.075***		
	(-41.72)	(-41.02)		
High W Fraction50			0.9399***	0.9396***
			(-16.02)	(-15.74)
Whole Loan × High W Fraction50			1.13***	1.13***
			(-22.84)	(-22.27)
Interest Rate	1.026***	1.027***	1.026***	1.027***
	(37.94)	(38.30)	(37.84)	(38.22)
Interest Rate^2	0.9995***	0.9995***	0.9995***	0.9995***
	(-22.96)	(-23.48)	(-23.12)	(-23.64)
DTI	0.9954***	0.9985***	0.9954***	0.9985***
	(-98.86)	(-33.69)	(-98.50)	(-33.33)
Amount Requested	1.012***	1.02***	1.012***	1.02***
	(23.66)	(35.77)	(24.48)	(36.53)
Utilization	0.9986***	0.9986***	0.9986***	0.9986***
	(-26.38)	(-24.93)	(-26.42)	(-24.96)
Utilization^2	1.00001***	1.00001***	1.00001***	1.00001***
	(14.42)	(12.40)	(14.47)	(12.44)
Inq6Month	1.019***	1.019***	1.019***	1.019***
	(40.07)	(39.09)	(40.37)	(39.38)
YrsFirstCredit	0.9991***	0.9991***	0.9991***	0.9991***
	(-20.94)	(-20.23)	(-21.18)	(-20.47)
5YearTerm	0.8699***	0.8703***	0.8704***	0.8708***
	(-151.5)	(-147.3)	(-151)	(-146.8)
Inverse of Fisher's Z	1.028E+28***	4.852E+33***	9.938E+27***	3.352E+33***
	(544.6)	(323)	(544.5)	(325.4)
Credit Grade FE	Yes	Yes	Yes	Yes
Employment Length FE	Yes	Yes	Yes	Yes
Loan Purpose FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Obs.	961,321	961,321	961,321	961,321

Panel B. First Stage Selection

	Loan Inclusion (Probit)			
	(1)	(2)	(3)	(4)
Debt-to-Income Ratio	1.056***	1.038***	1.056***	1.038***
	(-177)	(-144.7)	(-177)	(-144.7)
Amount Requested		0.8939***		0.8939***
		(-36.97)		(-36.97)
Total Supply		1.011*		1.011*
		(-1.662)		(-1.645)
CreditScoreRange 665-669	0.9082***	0.9236***	0.9083***	0.9236***
	(-12.04)	(-8.705)	(-12.04)	(-8.704)
CreditScoreRange 670-674	1.045***	1.056***	1.045***	1.056***
	(-5.289)	(-5.79)	(-5.288)	(-5.789)
CreditScoreRange 675-679	1.041***	1.053***	1.041***	1.053***
	(-4.552)	(-5.241)	(-4.55)	(-5.241)
CreditScoreRange 680-684	1.314***	1.277***	1.314***	1.277***
	(-28.56)	(-23.41)	(-28.56)	(-23.41)
CreditScoreRange 685-689	1.156***	1.164***	1.156***	1.164***
	(-15.27)	(-14.35)	(-15.27)	(-14.35)
CreditScoreRange 690-694	1.45***	1.4***	1.45***	1.399***
	(-34.85)	(-29.32)	(-34.84)	(-29.32)
CreditScoreRange 695-699	1.291***	1.272***	1.291***	1.272***
	(-24.39)	(-21.06)	(-24.39)	(-21.06)
CreditScoreRange 700-704	1.601***	1.542***	1.601***	1.542***
	(-39.56)	(-34.44)	(-39.55)	(-34.44)
CreditScoreRange 705-709	1.418***	1.396***	1.418***	1.395***
	(-29.86)	(-26.48)	(-29.85)	(-26.47)
CreditScoreRange 710-714	1.642***	1.57***	1.642***	1.57***
	(-37.52)	(-32.34)	(-37.51)	(-32.33)
CreditScoreRange 715-719	1.462***	1.429***	1.462***	1.428***
	(-28.91)	(-25.16)	(-28.9)	(-25.15)
CreditScoreRange 720-724	1.797***	1.697***	1.797***	1.697***
	(-37.9)	(-32.89)	(-37.9)	(-32.89)
CreditScoreRange 725-729	1.399***	1.388***	1.399***	1.388***
	(-22.55)	(-20.24)	(-22.54)	(-20.25)
CreditScoreRange 730-734	1.658***	1.591***	1.658***	1.591***
	(-29.15)	(-25.21)	(-29.14)	(-25.21)
CreditScoreRange 735-739	1.277***	1.262***	1.277***	1.262***
	(-14.57)	(-12.43)	(-14.57)	(-12.43)
CreditScoreRange 740-744	1.574***	1.53***	1.573***	1.53***
	(-23.05)	(-20.12)	(-23.05)	(-20.12)
CreditScoreRange 745-749	1.248***	1.241***	1.248***	1.241***
	(-11.83)	(-10.16)	(-11.82)	(-10.15)
CreditScoreRange 750-754	1.418***	1.400***	1.417***	1.400***
	(-16.57)	(-14.44)	(-16.56)	(-14.44)
CreditScoreRange 755-759	1.197***	1.197***	1.197***	1.197***
	(-8.978)	(-7.758)	(-8.972)	(-7.755)
CreditScoreRange 760-764	1.248***	1.25***	1.248***	1.25***
	(-9.888)	(-8.605)	(-9.889)	(-8.607)
CreditScoreRange 765-769	0.8683***	0.8998***	0.8682***	0.8998***
	(-7.518)	(-4.473)	(-7.52)	(-4.474)

Panel B. First Stage Selection (Continued)

	Loan Inclusion (Probit)			
	(1)	(2)	(3)	(4)
CreditScoreRange 770-774	1.295***	1.296***	1.295***	1.296***
	(-10.07)	(-8.716)	(-10.07)	(-8.717)
CreditScoreRange 775-779	1.137***	1.174***	1.137***	1.174***
	(-5.388)	(-5.571)	(-5.381)	(-5.567)
CreditScoreRange 780-784	1.156***	1.123***	1.156***	1.123***
	(-5.552)	(-3.664)	(-5.551)	(-3.664)
CreditScoreRange 785-789	0.9689	0.9578	0.9688	0.9578
	(-1.253)	(-1.336)	(-1.257)	(-1.338)
CreditScoreRange 790-794	1.161***	1.16***	1.16***	1.16***
	(-5.256)	(-4.24)	(-5.249)	(-4.236)
CreditScoreRange 795-799	0.944**	0.9441	0.9441**	0.9442
	(-2.023)	(-1.513)	(-2.02)	(-1.511)
CreditScoreRange 800-804	1.07**	1.074*	1.07**	1.074*
	(-2.215)	(-1.865)	(-2.214)	(-1.866)
CreditScoreRange 805-809	1.151***	1.118**	1.151***	1.118**
	(-3.948)	(-2.504)	(-3.946)	(-2.501)
CreditScoreRange 810-814	0.9195**	0.922*	0.9196**	0.9221*
	(-2.382)	(-1.719)	(-2.38)	(-1.716)
CreditScoreRange 815-819	1.067	1.079	1.067	1.079
	(-1.546)	(-1.38)	(-1.545)	(-1.38)
CreditScoreRange 820-824	0.8523***	0.94	0.8523***	0.94
	(-3.735)	(-1.081)	(-3.736)	(-1.08)
CreditScoreRange 825-829	0.9101*	0.9158	0.9099*	0.9157
	(-1.857)	(-1.281)	(-1.863)	(-1.283)
CreditScoreRange 830-834	0.6501***	0.7471***	0.65***	0.7471***
	(-8.771)	(-3.991)	(-8.773)	(-3.992)
CreditScoreRange 835-839	0.3733***	0.3555***	0.3732***	0.3554***
	(-22.79)	(-12.21)	(-22.79)	(-12.21)
CreditScoreRange 840-844	0.4041***	0.4416***	0.4041***	0.4416***
	(-17.07)	(-8.743)	(-17.06)	(-8.742)
CreditScoreRange 845-850	0.2867***	0.3001***	0.2866***	0.3000***
	(-25.98)	(-12.67)	(-25.98)	(-12.67)
Credit Grade FE	No	No	No	No
Employment Length FE	No	Yes	No	Yes
Loan Purpose FE	No	No	No	No
Year-Quarter FE	No	No	No	No
Obs.	961,321	961,321	961,321	961,321

Table 6. Multinomial Logit Competing Hazards: Default and Prepayment

We estimate competing hazards of default and prepayment using a multinomial logit model for the sample period 9/21/2014–12/31/2017. The model assumes a quadratic baseline hazard, columns (1)–(2), or a fifth order baseline in columns (3)–(4). Our variable of interest is *Whole Loan* which is an indicator for loans that are initially assigned to be funded in the institutional (whole loan) market. *High W Fraction* is equal to one if the dollar fraction of loans initially assigned to institutional investors is larger than the sample median. The models include indicators for credit grade, employment length, loan purpose, and quarter-year fixed effects. The *z*-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Outcome	Default	Prepayment	Default	Prepayment
	(1)	(2)	(3)	(4)
Whole Loan	0.9156***	0.8858***	0.9118***	0.886***
	(-4.922)	(-7.343)	(-5.124)	(-7.283)
High W Fraction	0.7014***	0.6598***	0.707***	0.6672***
	(-16.21)	(-20.88)	(-15.83)	(-20.35)
Whole Loan × High W Fraction	1.12***	1.211***	1.131***	1.218***
	(-4.66)	(-8.647)	(-5.056)	(-8.887)
Time (days)	0.9158***	0.9125***	0.7977***	0.7769***
	(-169.6)	(-176.8)	(-25.58)	(-28.57)
Time^2	1***	1***	1***	1.001***
	(-61.56)	(-76.28)	(-18.27)	(-22.29)
Time^3			1.000***	1.000***
			(-19.94)	(-25.11)
Time^4			1.000***	1.000***
			(-22.08)	(-28.55)
Time^5			1.000***	1.000***
			(-23.8)	(-31.54)
Interest Rate	1.198***	0.9272***	1.19***	0.923***
	(-15.79)	(-7.604)	(-15.22)	(-8.064)
Interest Rate^2	0.9981***	1.004***	0.9985***	1.004***
	(-5.81)	(-12.16)	(-4.798)	(-12.91)
DTI	1.0003***	0.9927***	1.0003***	0.9929***
	(-2.889)	(-24.77)	(-2.83)	(-23.99)
Amount Requested	1.1***	1.009	1.099***	1.008
	(-11.08)	(-1.165)	(-10.97)	(-1.068)
Utilization	1.003***	0.994***	1.003***	0.9942***
	(-3.444)	(-7.712)	(-3.671)	(-7.404)
Utilization^2	0.999***	1.00003***	0.999***	1.00003***
	(-3.039)	(-3.823)	(-3.256)	(-3.567)
Inq6Month	1.09***	1.016***	1.09***	1.016***
	(-13.36)	(-2.59)	(-13.33)	(-2.656)
YrsFirstCredit	0.9959***	1.001	0.9957***	1.001
	(-5.753)	(-1.544)	(-5.994)	(-1.547)
5YearTerm	0.4144***	0.2824***	0.3941***	0.2726***
	(-57.75)	(-89.35)	(-60.43)	(-91.03)
Constant	4.351E+36***	9.796E+38***	9.621E+48***	1.05E+52***
	(-196.5)	(-215.3)	(-74.28)	(-78.82)
Credit Grade FE	Yes	Yes	Yes	Yes
Employment Length FE	Yes	Yes	Yes	Yes
Loan Purpose FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Observations	1,355,815	1,355,815	1,355,815	1,355,815

Table 7. Credit Screen Rejection and Aggregate Default Response to Institutional Investor Loan Demand

In columns (1)–(3), we estimate a Probit model of the likelihood a loan application will be rejected by the platform's credit screening process. We report the coefficient estimates of the odds ratio in columns (1)–(3). Using the combination of rejected loan applications and loans that are allocated for funding, we create the dependent variable (*Rejection*) equal to one if the loan is rejected by the platform. In columns (4)–(6) we use only the sample of loans that pass the credit screen to estimate a Cox proportional hazard model for default and report the hazard ratios, i.e. the exponential form of the coefficients. In the specifications we include *W Amount* which is the daily dollar amount initially assigned to institutional investors. *Total Supply* is the daily aggregate dollar volume of loan applications (rejected and accepted) on the platform. Additional loan/borrower characteristics include *Interest Rate*, *Interest Rate*^{2}, *Utilization*, *Utilization*^{2}, *Inq6Month*, *YrsFirstCredit*, and *5YearTerm*. The models in columns (1)–(3) include indicators for FICO score range, employment length, and quarter-year fixed effects. The models in columns (4)–(6) include indicators for credit grade, employment length, loan purpose, and quarter-year fixed effects. The *z*-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Outcome		Rejection			Default	
Model		Probit			Cox	
	(1)	(2)	(3)	(4)	(5)	(6)
Log(W Amount)	0.7203***			1.021***		
	(-87.24)			(-4.462)		
W Amount / 1,000,000		0.9814***			1.002***	
		(-81.79)			(-8.628)	
High W Amount			0.8066***			1.001
			(-46.67)			(-0.1576)
Total Supply	1.237***	1.327***	1.207***			
	(-14.34)	(-18.8)	(-12.44)			
DTI	0.9738***	0.9739***	0.9739***	1.0001***	1.0001***	1.0001***
	(-136.7)	(-136.4)	(-137)	(-2.738)	(-2.698)	(-2.753)
Amount Requested	1.163***	1.163***	1.16***	1.117***	1.117***	1.117***
	(-67.48)	(-67.57)	(-66.40)	(-27.21)	(-27.23)	(-27.19)
Employment Length FE	Yes	Yes	Yes	Yes	Yes	Yes
FICO Score Range FE	Yes	Yes	Yes	No	No	No
Additional Loan/Borrower Characteristics	No	No	No	Yes	Yes	Yes
Credit Grade FE	No	No	No	Yes	Yes	Yes
Loan Purpose FE	No	No	No	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	1,531,564	1,531,564	1,531,564	774,214	774,214	774,214

Table 8. Regulatory Scrutiny around San Bernardino Shooting

This table reports Cox proportional hazard ratios for default, i.e. the exponential form of the coefficients for loans originated on LendingClub during the 120 days before and after the San Bernardino shooting news release on 12/8/15. 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. Our variable of interest is *Whole Loan* which is an indicator for loans that are initially assigned to be funded in the institutional (whole loan) market and *Post* which is an indicator for the 120 days following the news release on 12/8/15. *High W Fraction* is equal to one if the dollar fraction of loans initially assigned to institutional investors is larger than the sample median. All the models contain indicators for credit grade, employment length, 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.

	(1)	(2)	(3)
Whole Loan	0.9436***	0.9235***	0.9154***
	(-4.351)	(-5.258)	(-5.453)
Post	0.8514***	0.8806***	0.8754***
	(-7.753)	(-5.731)	(-4.27)
Whole Loan × Post	1.117***	1.072***	1.115***
	(-5.68)	(-3.111)	(-3.000)
High W Fraction		0.9114***	0.9095***
		(-4.855)	(-3.868)
High W Fraction × Whole		1.088***	1.112***
		(-3.77)	(-3.727)
High W Fraction × Post			1.008
			(-0.2017)
High W Fraction × Post × Whole			0.9445
			(-1.239)
Interest Rate	1.281***	1.281***	1.281***
	(-18.35)	(-18.30)	(-18.31)
Interest Rate^2	0.9963***	0.9963***	0.9963***
	(-9.003)	(-8.929)	(-8.925)
Debt-to-Income Ratio	1.00009**	1.00009**	1.00009**
	(-2.501)	(-2.511)	(-2.504)
Amount Requested	1.105***	1.105***	1.105***
	(-13.2)	(-13.19)	(-13.19)
Creditline Utilization	0.9923***	0.9923***	0.9923***
	(-10.37)	(-10.38)	(-10.38)
Creditline Utilization^2	1.00002***	1.00002***	1.00002***
	(-3.19)	(-3.199)	(-3.196)
No. of Inquiries Last 6 month	1.088***	1.088***	1.088***
	(-18.91)	(-18.91)	(-18.9)
No. of Years Since First Credit	0.9919***	0.9919***	0.9919***
	(-13.3)	(-13.32)	(-13.32)
Duration 60 Months	0.477***	0.476***	0.4761***
	(-65.55)	(-65.71)	(-65.65)
Employment Length FE	Yes	Yes	Yes
Credit Grade FE	Yes	Yes	Yes
Loan Purpose FE	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes
Obs.	158,209	158,209	158,209

Table 9. Asset-Backed Security Pools from Marketplace Lending Loans

Panel A displays the FICO distribution for the three ABS issues backed by LendingClub loans in our sample period. Panel B reports default hazard ratios for loans originated on LendingClub during the period 9/21/2014–12/31/2017. 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. Our variable of interest is *Whole Loan* which is an indicator for loans that are initially assigned to be funded in the institutional (whole loan) market and *ABS Activity* which is an indicator signifying when ABS issuers were most likely purchasing loans for an ABS issue (see Figure 5). We divide the sample by borrower FICO score corresponding with the FICO score ranges in Panel A. All the models contain the same set of loan/borrower characteristics in Table 3 in addition to indicators for credit grade, employment length, 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.

Panel A. FICO Distribution of ABS backed by LendingClub Loans

ARCT 2017-1		CLUB 2017-P1		CLUB 2017-P2	
660–679	45.84%	660–679	42.22%	660–679	27.55%
680–699	27.78%	680–699	26.60%	680–699	26.11%
700–719	17.06%	700–719	15.67%	700–719	20.49%
720–739	6.24%	720–739	7.96%	720–739	12.82%
740–759	1.87%	740–759	3.81%	740–759	6.14%
760–779	0.72%	760–779	2.03%	760–779	3.32%
780+	0.50%	780–799	1.01%	780–799	2.04%
		800–819	0.52%	800–819	1.05%
		820–More	0.19%	820–More	0.49%

Panel B. Cox Proportional Hazard Default Model by FICO Score Range

FICO Range	660-679	680-699	700-719	720-739	740-759	760-779	780-799	800-819	820+
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Whole Loan	0.9613***	0.9716***	0.9674**	0.974	0.980	0.9531	0.8671*	1.005	0.8768
	(-4.824)	(-2.735)	(-2.238)	(-1.115)	(-0.5271)	(-0.8394)	(-1.696)	(-0.0406)	(-0.5043)
ABS Activity	0.8496***	0.8861***	0.8858***	0.8109***	0.8513	0.8325	0.5433***	0.8936	1.598
	(-7.722)	(-4.312)	(-3.181)	(-3.319)	(-1.635)	(-1.276)	(-2.726)	(-0.3536)	(-0.916)
Whole Loan × ABS Activity	1.223***	1.215***	1.184***	1.307***	1.303**	1.263	1.777**	1.122	0.7744
	(-8.807)	(-6.507)	(-4.165)	(-4.052)	(-2.573)	(-1.563)	(-2.462)	(-0.3468)	(-0.4738)
Loan/Borrower Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Credit Grade FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Employment Length FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan Purpose FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	268,927	206,372	142,721	77,197	38,195	20,676	11,585	6,165	2,252

Table 10. Loan Default during Securitization Activity and Heavy Institutional Loan Demand

This table reports default hazard ratios for loans originated on LendingClub during the period 9/21/2014–12/31/2017. Our variable of interest is *Whole Loan* which is an indicator for loans that are initially assigned to be funded in the institutional (whole loan) market and *ABS Activity* which is an indicator signifying when ABS issuers were most likely purchasing loans for an ABS issue (see Figure 5). *High W Fraction** is equal to one if the dollar fraction of loans initially assigned to institutional investors is larger than the sample median. *High W Fraction MA30** is equal to one if the 30-day moving average of the dollar fraction of loans initially assigned to institutional investors is larger than the sample median. When *High W Fraction** (*High W Fraction MA30**) and *ABS Activity* are both one, we set *High W Fraction** (*High W Fraction MA30**) equal to zero. In columns (3)–(4) we divide *ABS Activity* into three indicators, one for each ABS issue shown in Table 9 Panel A. All the models contain the same set of loan/borrower characteristics in Table 3 in addition to indicators for credit grade, employment length, 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.

	(1)	(2)	(3)	(4)
Whole Loan	0.9186***	0.8872***	0.967***	0.9181***
	(-12.53)	(-17.43)	(-5.957)	(-12.6)
ABS Activity	0.8268***	0.9651**		
	(-12.32)	(-2.262)		
Whole Loan × ABS Activity	1.147***	1.053***		
	(-8.244)	(-3.006)		
High W Fraction*	0.9027***			0.9018***
	(-10.77)			(-10.83)
Whole Loan × High W Fraction*	1.155***			1.156***
	(-14.13)			(-14.18)
High W Fraction MA30*		0.8106***		
		(-18.96)		
Whole Loan × High W Fraction MA30*		1.282***		
		(-21.88)		
ABS Activity: ARCT 2017-1			0.8688***	0.8428***
			(-7.182)	(-8.513)
ABS Activity: LC CLUB-P1			0.8866***	0.8521***
			(-4.52)	(-5.911)
ABS Activity: LC CLUB-P2			0.7832***	0.7556***
			(-6.865)	(-7.759)
Whole Loan × ABS ARCT 2017-1			1.19***	1.101***
			(-8.364)	(-4.473)
Whole Loan × ABS LC CLUB-P1			1.263***	1.19***
			(-8.478)	(-6.239)
Whole Loan × ABS LC CLUB-P2			1.374***	1.253***
			(-8.488)	(-5.939)
Loan/Borrower Characteristics	Yes	Yes	Yes	Yes
Credit Grade FE	Yes	Yes	Yes	Yes
Employment Length FE	Yes	Yes	Yes	Yes
Loan Purpose FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Obs.	774,214	774,214	774,214	774,214

Table 11. Alternative Platform Robustness: Prosper Loan Default based on Initial Assignment

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 in columns (1) and (4)–(6). We estimate an Exponential model and a Weibull model for default in columns (2) and (3) respectively. Our variable of interest is *Whole Loan* which is an indicator for loans that are initially assigned to be funded in the institutional (whole loan) market and *ABS Activity* which is an indicator signifying when ABS issuers were most likely purchasing loans for an ABS issue (see Figure 5). *High W Fraction* is equal to one if the dollar fraction of loans initially assigned to institutional investors is larger than the sample median. *High W Fraction** is equal to one if the dollar fraction of loans initially assigned to institutional investors is larger than the sample median. When *High W Fraction** and *ABS Activity* are both one, we set *High W Fraction** equal to zero. *ABS Internal Period* is an indicator of the ABS issues where Prosper is the ABS issuer. All the models contain indicators for employment length, 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.

	Cox	Exponential	Weibull		ABS Activity	
	(1)	(2)	(3)	(4)	(5)	(6)
Whole Loan	1.015	1.011	1.011	0.9948	0.952	0.9749
	(-0.847)	(-0.6402)	(-0.6515)	(-0.234)	(-1.636)	(-0.9658)
High W Fraction				1.000		
				(-0.0025)		
Whole Loan × High W Fraction				1.029		
				(-0.7908)		
ABS Activity					0.9124**	0.9052***
					(-2.495)	(-2.905)
Whole Loan × ABS Activity					1.109***	1.082**
					(-2.749)	(-2.267)
High W Fraction*					1.023	
					(-0.405)	
Whole Loan × High W Fraction*					1.028	
					(-0.4903)	
ABS Internal Period						0.9714
						(-0.2968)
Whole Loan × ABS Internal Period						0.9413
						(-0.6599)
ABS Activity × ABS Internal Period						0.8894
						(-0.78)
Whole Loan × ABS Activity × ABS Internal Period						1.008
						(-0.0493)

Table 11. Alternative Platform Robustness: Prosper Loan Default based on Initial Assignment (Continued)

	Cox	Exponential	Weibull		ABS Activity	
	(1)	(2)	(3)	(4)	(5)	(6)
Lender Yield	1.192***	1.191***	1.192***	1.192***	1.193***	1.192***
	(-14.15)	(-14.07)	(-14.15)	(-14.13)	(-14.2)	(-14.14)
Lender Yield^2	0.9981***	0.9981***	0.9981***	0.9981***	0.9981***	0.9981***
	(-5.74)	(-5.788)	(-5.738)	(-5.726)	(-5.814)	(-5.767)
DTI	1.000	1.000	1.000	1.000	1.000	1.000
	(-0.2452)	(-0.2488)	(-0.2359)	(-0.2484)	(-0.2786)	(-0.2763)
Amount Requested	1.162***	1.161***	1.165***	1.162***	1.162***	1.162***
	(-18.42)	(-18.35)	(-18.77)	(-18.43)	(-18.4)	(-18.39)
Utilization	0.9966***	0.9966***	0.9965***	0.9966***	0.9966***	0.9966***
	(-4.262)	(-4.259)	(-4.333)	(-4.26)	(-4.256)	(-4.256)
Utilization ^{2}	1.000	1.000	1.000	1.000	1.000	1.000
	(-0.5252)	(-0.5489)	(-0.5397)	(-0.522)	(-0.518)	(-0.519)
Inq6Month	1.090***	1.089***	1.091***	1.09***	1.090***	1.090***
	(-24.29)	(-24.08)	(-24.63)	(-24.29)	(-24.26)	(-24.27)
YrsFirstCredit	0.9903***	0.9903***	0.9901***	0.9903***	0.9903***	0.9903***
	(-15.2)	(-15.16)	(-15.49)	(-15.2)	(-15.19)	(-15.2)
5YearTerm	0.6733***	0.6977***	0.6795***	0.6733***	0.6733***	0.6733***
	(-34.99)	(-32.18)	(-34.43)	(-34.99)	(-34.99)	(-34.98)
Credit Grade FE	Yes	Yes	Yes	Yes	Yes	Yes
Employment Length FE	Yes	Yes	Yes	Yes	Yes	Yes
Loan Purpose FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	164,779	164,779	164,779	164,779	164,779	164,779

Table 12. Reallocation of Whole Loans

This table reports default hazard ratios for loans originated on LendingClub during the reported in each column. 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 include an indicator (*Whole Funded*) equal to one if a loan is allocated to the whole loan market and funded by whole loan market investors. We also include an indicator (*Reallocated*) equal to one if a loan is initially assigned to the whole loan market but after some period is reallocated to the fractional market where it is funded. *High W Fraction* is equal to one if the dollar fraction of loans initially assigned to institutional investors is larger than the sample median. All the models contain the same set of loan/borrower characteristics in Table 3 in addition to indicators for credit grade, employment length, 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.

	Sept2014-Dec2017		Sept2014-Apr2016	
	(1)	(2)	(3)	(4)
Whole Funded	0.9916	0.9222***	0.9422***	0.9093***
	(-1.559)	(-11.61)	(-8.665)	(-11.51)
Reallocated	0.9887	0.8783***	1.023**	0.9213***
	(-1.095)	(-8.762)	(-1.993)	(-5.156)
High W Fraction		0.8718***		0.9001***
		(-14.5)		(-8.071)
Whole Funded × High W Fraction		1.203***		1.135***
		(-17.37)		(-8.806)
Reallocated × High W Fraction		1.317***		1.279***
		(-13.48)		(-10.89)
Loan/Borrower Characteristics	Yes	Yes	Yes	Yes
Employment Length FE	Yes	Yes	Yes	Yes
Credit Grade FE	Yes	Yes	Yes	Yes
Loan Purpose FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Obs.	774,214	774,214	263,559	263,559

Internet Appendix

IA1.1 Interest Rate Comparison

In the main body of the paper, we examine loan allocation practices of marketplace lending platforms and mainly test for differences in default rates between loans allocated to retail and institutional investors. Our main tests show that platforms preferentially allocate loans with lower default rates to institutional investors but during periods of high institutional loan demand the platforms also protect retail investors through preferential loan allocation. In the main specifications, we control for the information contained in interest rates assigned to a loan. An alternative scheme of preferential allocation could be implemented if platforms allocate loans with similarly expected default but different interest rates. We test for such behavior in Table A1 for LendingClub (Panel A) and Prosper (Panel B). In addition to loan characteristics and borrower characteristics, we obtain macro-economic data from the St. Louis Federal Reserve FRED Economic Data set including Treasury rates and Moody's corporate bond yield. We also include credit grade fixed effects interacted with date fixed effects which should allow us to remove any risk premium driven by the macro-economy. The results in Table A1 show that both platforms fairly assign interest rates prior to allocating the loans for investors. The indicator for whole loan assignment is insignificant in all the specifications reported.

IA1.2 Prosper Data Sample Creation

When conducting our tests in Table 11, we use data from an alternate marketplace lending platform in the U.S. called Prosper. Our Prosper loan sample is composed of all the loans originated in the whole loan market and the fractional market for the period 3/25/13 through 2017. We gather multiple data sets from the platform. First, the platform provides a loan issuance file that includes details on the borrower's credit profile and loan details at the time the loan is originated. Prosper identifies the initial funding market (fractional, whole) where the loan is listed. We gather borrower credit information, number of inquiries in the past six months, number of years since first credit is established, credit line utilization, and debt-to-income ratio of the borrower. We also capture loan details: the amount requested by the borrower, interest rate assigned by the platform to the loan, platform credit rating, term, and the loan purpose. Prosper provides timestamps for initiation and funding completion specifically for the whole loan market. We assume any loans that are posted in the whole loan market but do not have a funding timestamp in the whole loan market are rolled over to the fractional market.

The second set of data obtained from the platform is loan outcome data. Prosper provides information on the current status of a loan as of 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.[25] We verify the validity of this approach using a previously available loan outcome file similar to the one available for LendingClub and find it to be a good approximation of loan outcome and survival.[26]

Prosper does not provide access to an application rejection file. However, on the Prosper platform, loans that pass through both the fractional and whole loan market unfunded are not funded by the platform. Borrowers' loan applications are removed from the platform and the loan request is denied.

Securitization data is sourced from the same vendors. 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 issue date (24.7 days). This methodology allows us to estimate when loans included in the pool were likely to be originated.

IA1.3 Identification of Re-Allocated Loans and Origination date collection

LendingClub loan-level information is filed with the SEC to provide the public with a source of information on the potential investment. Initially, the platform submits loan/borrower details to the SEC through a Form 424(B)(3) filing when the borrower's loan request has passed the platform's initial credit screen (see Figure 1). We collect data from the SEC on loans listed for funding and match that to the data provided by the platform. The platform identifies these loans as "listed" loans. The platform also files a second Form 424(B)(3) registration update with the SEC for the loans that are successfully funded (sold)

[25] 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.

[26] 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.

through the retail active market (Figure 1 item (5)). The platform is only required to file an update for loans that fractional (retail) 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 (2) and (3)) versus loans that are initially assigned to the whole loan market but are reallocated to the fractional market (Figure 1 item (4)). Through the sold loan filings, we are also able to collect the issue/origination date of retail funded loans. To collect issue/origination date for whole loans, we use the information provided by the platform's data file URL links.

IA1.4 Prepayment of loans

In addition to default, investors may also be concerned with borrower prepayment as it creates reinvestment risk. Given the short maturities of personal unsecured loans, this is likely less a concern relative to other assets such as residential mortgages. Complicating the issue, if prepayment and default are negatively correlated, investors may be willing to accept such a tradeoff. However, we anticipate lower prepayment is advantageous after netting out effects driven by its correlation with default. In the main body of the paper, we show that institutions are allocated loans with lower prepayment in Table 6 columns (2) and (4) after addressing the correlation between prepayment and default. Similar to default, we show that retail investors are protected during periods of high institutional loan demand. Retail investors are allocated lower prepaying loans at the expense of institutional investors.

For completeness, we present a companion table to Tables 3, modeling prepayment hazard similar to the key tests presented in the main body of the paper for default hazard. Table A3 shows the prepayment hazard for the full sample of loans in column (1) and the subsamples split by credit grade category (2)–(3) and term (4)–(5). Similar to Table 3, the results in column (1) show no preferential treatment of institutional investors. The hazard ratio in column (2) also suggests institutional investors and retail investors bear similar prepayment risk in investment-grade loans. However, column (3) suggests in the riskier high yield loan segment, whole loan investors are allocated loans with a 3.9% higher prepayment hazard. Column (4) suggests a similar early prepayment hazard for institutional investors in shorter term loans, while column (5) indicates no difference in loan allocation among five-year notes. For the case of prepayment, these estimates show the importance of competing hazards as the direction of our results switch relative to Table 6. Given the inverse relationship between prepayment and default shown in the mortgage literature, this is not entirely surprising.

Table A1. Interest Rate Comparison

This table reports the OLS regression results of interest rates regressed on the platforms' initial funding assignment. Panel A presents results for LendingClub while Panel B presents results for Prosper. Column (1) examines the full sample of loans and we split the sample by credit grade category in columns (2)–(3) consistent with the main tables in the paper. We include U.S. Treasury rates with one-year maturity (*Treasury Rate*). *Term Spread* is the yield spread between ten-year and one-year Treasury rate. *Credit Spread* is the spread between Moody's Baa corporate bond yield and the yield on 10-year Treasury notes, *Total Demand* is the log value of total dollar amount of loan applications (rejected loans plus accepted loans) and used when available. All the models contain indicators for employment length, loan purpose, and credit grade interacted with the date. *t*-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A. LendingClub

Dependent variables	Interest Rate		
Credit Grade	All	ABCD	EFG
Whole Loan	-0.00125	-0.00284	0.00496
	(-0.547)	(-1.184)	(-0.638)
Treasury Rate	51.79	119.1	6.248
	(-0.005)	(-0.201)	(-0.000)
Term Spread	61.06	133.5	-5.61
	(-0.0036)	(-0.114)	(-0.000)
Credit Spread	-86.93	-112.1	22.51
	(-0.004)	(-0.048)	(-0.001)
Total Supply	-1.349	3.42	-0.475
	(-0.002)	(-0.091)	(-0.000)
Debt-to-Income Ratio	0.0003***	0.0003***	0.0001*
	(-12.91)	(-13.32)	(-1.909)
Amount Requested	-0.011***	-0.014***	0.016***
	(-7.357)	(-8.703)	(-2.592)
Creditline Utilization	0.008***	0.008***	-0.001
	(-51.45)	(-52.77)	(-1.491)
Creditline Utilization^2	-0.00004***	-0.00004***	0.00001***
	(-23.63)	(-23.82)	(-2.746)
No. of Inquiries Last 6 month	0.0903***	0.0986***	0.0363***
	(-80.11)	(-80.92)	(-12.06)
No. of Years Since First Credit	-0.009***	-0.009***	-0.005***
	(-67.98)	(-67.84)	(-10.21)
Duration 60 Months	0.283***	0.283***	0.286***
	(-110.9)	(-106.6)	(-31.59)
Constant	76.26	-148.8	-8.719
	(-0.004)	(-0.095)	(-0.000)
Employment Length FE	Yes	Yes	Yes
Credit Grade × Day FE	Yes	Yes	Yes
Loan Purpose FE	Yes	Yes	Yes
Observations	1,347,796	1,040,859	306,937
R-squared	0.952	0.917	0.911

Panel B. Prosper

Dependent Variable	Lender Yield		
Credit Grade	All	AA-C	D-HR
	(1)	(2)	(3)
Whole Loan	0.00172	0.00908	-0.00208
	(-0.194)	(-0.905)	(-0.144)
Treasury Rate	32.85	3.483	22.82
	(-0.002)	(-0.0001)	(-0.001)
Term Spread	13.57	-0.064	4.972
	(-0.002)	(-0.000)	(-0.001)
Credit Spread	-1.173	-0.264	8.168
	(-0.000)	(-0.000)	(-0.000)
Debt-to-Income Ratio	0.0001***	0.010***	0.0001***
	(-4.711)	(-36.53)	(-2.755)
Amount Requested	-0.031***	-0.0621***	-0.044***
	(-8.206)	(-15.25)	(-6.597)
Creditline Utilization	0.003***	0.004***	0.000
	(-8.278)	(-11.22)	(-0.096)
Creditline Utilization^2	0.002***	0.002***	0.004***
	(-5.315)	(-4.144)	(-6.49)
No. of Inquiries Last 6 month	0.068***	0.097***	0.054***
	(-34.72)	(-41.77)	(-17.5)
No. of Years Since First Credit	-0.003***	-0.005***	-0.002***
	(-9.72)	(-15.12)	(-3.805)
Duration 60 Months	0.260***	0.398***	0.200***
	(-46.35)	(-59.65)	(-22.31)
Constant	-16.17	7.301	-16.75
	(-0.000)	(-0.000)	(-0.000)
Employement Length FE	Yes	Yes	Yes
Credit Grade × Day FE	Yes	Yes	Yes
Loan Purpose FE	Yes	Yes	Yes
Observations	237,058	123,432	113,626
R-squared	0.961	0.876	0.901

Table A2. Regulatory Scrutiny—Media Citations

This table provides media citations connecting the San Bernardino shooting event to Prosper/WebBank. It also references media stories discussing the increased regulatory scrutiny following the event.

Quote	Coverage	Source
"Online lending platform Prosper Marketplace Inc. arranged a loan for Syed Rizwan Farook a few weeks before he and his wife allegedly opened fire on an office holiday party in San Bernardino, California, according to a person with knowledge of the matter. Prosper, which matches borrowers with investors who want to fund them, declined to comment, citing privacy laws, when reached by Bloomberg. Investigators of the massacre are examining a $28,500 deposit into Farook's bank account in mid-November and whether it was used to buy guns, Fox News reported Tuesday, citing an unidentified person close to the investigation. While there's no indication that Prosper is suspected of any wrongdoing, its role in providing cash to the alleged shooters risks stoking the already mounting debate over whether Internet loan platforms are adequately regulated."	Initial Event	Bloomberg 12/8/15 https://www.bloomberg.com/news/articles/2015-12-08/prosper-said-to-arrange-loan-to-san-bernardino-shooter-weeks-ago
"A separate source told Reuters that Prosper, a San Francisco-based online lender, made a $28,500 collateral-free loan to Farook in mid-November. Loans made by Prosper, which processes borrowers' applications and evaluates their credit-worthiness, are originated by the third-party bank WebBank, based in Salt Lake City. Prosper then sells its loans to investors."	Initial Event	Reuters 12/8/15 https://www.reuters.com/article/us-california-shooting-account-idUSKBN0TR27P20151209
"Prosper finds prospective borrowers and sells loans they take out through its website to investors but doesn't directly extend any credit. Rather, Prosper loans are originated by WebBank, a Salt Lake City, Utah-based bank that is owned by conglomerate Steel Partners Holdings LP. WebBank 'sets all compliance policies and procedures and supervises the entirety of each program' it has entered into with a marketplace lender, the bank's executive chairman, John McNamara, said in a September comment letter to the U.S. Treasury. The bank said in a statement Tuesday that federal and state law prevents WebBank from publicly commenting on any specific borrower but that it evaluates all applications in accordance with legal requirements, including antiterrorism and antimoney laundering laws. WebBank added that it will fully cooperate with law enforcement agencies investigating this matter."	Initial Event	WSJ 12/8/15 https://www.wsj.com/articles/san-bernardino-shooter-took-out-28-500-loan-prior-to-terror-attack-source-says-1449608166
"' This is certainly not a good storyline to be associated with,' Morningstar analyst Timothy Puls told Reuters. 'There's not a whole lot of regulation on this industry and we think that's coming.' The U.S. Treasury Department earlier this year signaled it is scrutinizing the growth of the online lending market when it issued what is known as a request for information, a move that could be a first step toward more regulation of the industry."	Initial Event	NBC 12/9/15 https://www.nbcnews.com/storyline/san-bernardino-shooting/san-bernardino-shooter-

		received-funds-through-online-lending-site-n477046
"…California Rep. Maxine Waters, the top Democrat on the House Financial Services Committee, re-introduced a bill … to make bank executives personally liable for violations of anti-money laundering and bank secrecy act provisions. 'Given the recent horrific acts of violence carried out by the San Bernardino shooters, and with the Islamic State having demonstrated both the capacity and intention to export its brutality beyond the Middle East,' Waters said in a statement announcing the bill, 'the need to sharpen our anti-terrorism financing and anti-money laundering efforts has become increasingly urgent. ' "	Post Event Regulatory Scrutiny	USA Today 12/15/2015 https://www.usatoday.com/story/money/2015/12/15/shooting-terrorism-online-loans-san-bernardino/77358520/
"…More troubling for Lending Club and its competitors, however, may be the mounting government scrutiny over their fast-growing and largely unregulated industry. The marketplace lending sector, for which Lending Club is the largest and most prominent poster child, is facing increased attention from several government bodies, including the Treasury Department and the Consumer Financial Protection Bureau. Then, in December, the entire industry started hearing accusations of guilt by association in the San Bernardino shootings. One of the shooters, Syed Rizwan Farook, took out a Prosper loan for $28,500 weeks before the suspected terrorist attacks, in which 14 people were killed. Federal officials have said that the Prosper loan may have helped Farook pay for ammunition and target practice. State and federal officials promptly took note. "Just looking at what we know, it seems like the type of loan any bank would have made," Laplanche told me last week. "I don't know what else could have been done by Prosper or WebBank [which originates Prosper loans] or any other bank." Laplanche's comments were echoed last week by Prosper founder Chris Larsen, who left the company several years ago and is now running a digital payments-related startup, Ripple."	Post Event Regulatory Scrutiny	Inc. 1/15/16 https://www.inc.com/maria-aspan/lending-club-ceo-on-rough-first-public-year.html
"…The Consumer Financial Protection Bureau this week called for borrowers to alert the federal agency of any complaints they have about the firms, a move seen in the industry as a potential prelude to further action by the consumer watchdog. 'It's likely a signal that the bureau has decided to send to companies: Watch out, our eyes are on you,' said Scott Pearson, a partner in the Los Angeles office of law firm Ballard Spahr who represents marketplace lenders. 'It's a sign that the regulators are paying attention to what marketplace lenders are doing.' The CFPB's call for complaints comes the same week that California officials are moving forward with a broad inquiry into the online lending business. Both the state Department of Business Oversight and the CFPB have turned their attention to so-called marketplace or peer-to-peer lenders — online firms that offer loans to consumers and small businesses, then sell those loans to investors."	Post Event Regulatory Scrutiny	LA Times 3/9/16 https://www.latimes.com/business/la-fi-online-lending-regulations-20160309-story.html

Table A3. Hazard Models of Loan Prepayment Based on Initial Market Assignment

This table reports prepayment hazard ratios for loans originated on LendingClub during the reported in each column. Hazard ratios greater than one suggest the variables have a positive association with prepayment while ratios less than one have a negative association with prepayment. We estimate a Cox proportional hazard model for prepayment. We include an indicator (*Whole Funded*) equal to one if a loan is allocated to the whole loan market and funded by whole loan market investors. Column (1) uses the full sample of loans, and in column (2)–(3) we split the sample by credit grade category and loan term in columns (5)–(6). All the models contain indicators for credit grade, employment length, 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.

Model		Credit Grade		Term	
	(1)	(2)	(3)	(4)	(5)
	Full	ABCD	EFG	36 Term	60 Term
Whole Loan	1.004	0.9981	1.039***	1.017***	1.009
	(-1.295)	(-0.6118)	(-3.542)	(-5.228)	(-1.127)
Interest Rate	0.995*	1.001	0.9312***	1.011***	1.055***
	(-1.784)	(-0.275)	(-4.112)	(-3.169)	(-7.321)
Interest Rate^2	1.002***	1.002***	1.002***	1.001***	1.000
	(-25.01)	(-12.24)	(-5.913)	(-8.368)	(-0.5907)
Debt-to-Income Ratio	0.9945***	0.9947***	0.9921***	0.9958***	0.9911***
	(-35.39)	(-32.64)	(-15.04)	(-24.42)	(-25.78)
Amount Requested	1.006***	1.001	1.100***	0.9934***	1.077***
	(-2.968)	(-0.3204)	(-10.71)	(-2.976)	(-9.138)
Creditline Utilization	0.9869***	1.043***	1.04***	1.042***	1.047***
	(-61.51)	(-24.81)	(-8.748)	(-23.04)	(-12.88)
Creditline Utilization^2	1.000***	0.9962***	0.999	0.9966***	0.9948***
	(-32.33)	(-20.31)	(-1.373)	(-17.06)	(-11.92)
No. of Inquiries Last 6 month	1.043***	0.9864***	0.9915***	0.9866***	0.9851***
	(-26.59)	(-61.45)	(-10.56)	(-56.43)	(-30.64)
No. of Years Since First Credit	0.9964***	1.00007***	1.00002**	1.00007***	1.00006***
	(-19.6)	(-33.26)	(-2.556)	(-31.98)	(-12.84)
Duration 60 Months	0.4039***	0.3796***	0.5694***		
	(-221.5)	(-219.8)	(-43.16)		
Credit Grade FE	Yes	Yes	Yes	Yes	Yes
Employment Length	Yes	Yes	Yes	No	No
Loan Purpose FE	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes
Obs.	1,173,355	1,090,540	82,815	853,510	319,845