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Spillover Effects of Peer-to-Peer Lending on the Loan Losses of Commercial Banks

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Abstract

Financial technology (FinTech) companies are increasingly important in the financial system. We investigate the effect of peer-to-peer (P2P) lending on traditional banks' loan losses by examining whether and how P2P lending activity in a state affects loan loss provisions of that state's commercial banks. If P2P lending helps borrowers repay their bank loans, banks might report lower loan loss provisions. However, if P2P lending results in higher leveraged borrowers, banks might accrue higher loan loss provisions. Using a large sample of US single-state banks during 2009-2017, we find that banks in states where P2P lending volume is higher report higher loan loss provisions. This positive relation is stronger for banks with greater exposure to the consumer loan market and for banks whose consumer borrowers are already more leveraged. These findings support the overleveraging effect of P2P lending on banks' consumer borrowers. We also find that P2P lending is associated with higher future loan charge-offs, which capture realized loan losses. Overall, our study offers new insights into the interaction between FinTech firms and traditional financial institutions.

Keywords: financial technology; peer-to-peer lending; overleverage; commercial banks; loan losses

JEL codes: G21, G23, G51, M41

I. INTRODUCTION

Financial technology (FinTech) companies play an increasingly important role in the financial system. The rapid development of the FinTech industry has received a great deal of attention from the financial press and regulators alike. Early studies in this area investigate how fund providers evaluate borrowers (e.g., Michels 2012; Duarte, Siegel, and Young 2012; Zhang and Liu 2012; Lin, Prabhala, and Viswanathan 2013). More recent studies consider the market mechanism (e.g., Wei and Lin 2017; Vallee and Zeng 2019; Du, Li, T. Lu, and X. Lu 2019) and the interaction between peer-to-peer (P2P) lending platforms and the traditional banking system (e.g., Butler, Cornaggia, and Gurun 2017; Cornaggia, Wolfe, and Yoo 2018; Tang 2019; Chava, Paradkar, and Zhang 2019). Studying this interaction is important because a borrower can typically choose to borrow from a bank, a P2P lending platform, or both. Hence, when P2P lending develops in a region, banks in that region might experience significant spillover effects. In addition, the delinquency rates at P2P lenders are, perhaps not surprisingly, higher than those at traditional banks.[1] To the extent that a borrower is a customer of both P2P lenders and banks, the borrower's default at one lender may create a spillover effect that affects other lenders.

In this paper, we aim to gain a better understanding of the spillover effects of P2P lending on the traditional banking sector by examining whether and how the development of P2P lending in a state affects the loan losses recorded by the commercial banks in that state. According to the rules for accounting for loan losses, loan loss provisions are estimated loan losses for the fiscal period and are the key component of total accruals in the banking industry (Beatty and Liao 2011, 2014). Loan loss provisions provide a timely indication of a bank's loan losses when it receives private information (e.g., notification of borrowers'

[1] The historical charge-off rate on loans originated by LendingClub, the largest US P2P platform, is around 10% (for loans issued during 2007Q1-2017Q4, the total issued loans = $26.07 billion and the net charge-offs = $2.69 billion; see https://www.lendingclub.com/info/demand-and-credit-profile.action), whereas the delinquency rate on US commercial banks' consumer loans is less than 5% (see https://fred.stlouisfed.org/series/DRCLACBS).

financial difficulties and nonrepayment of existing loans). Hence, we rely on loan loss provisions to examine the impact of P2P lending on the loan losses of commercial banks and we argue that the relation between P2P lending and banks' loan losses is an empirical issue.[2]

The bank loan repayment channel predicts a negative relation between P2P lending and banks' loan losses. FinTech helps to connect funding providers and borrowers and makes the loan screening process more effective. As one type of FinTech application, P2P lending platforms provide an easy, additional source of funding for individuals and households. This funding could be directly used to repay bank debt. In fact, most borrowers use P2P lending to refinance expensive bank debt (Balyuk 2019). Given the ease of applying for P2P loans, they can also be used to manage a short-term gap in cash flow. The availability of this source of additional funding, possibly even at a lower debt financing cost (Jagtiani and Lemieux 2019; Balyuk 2019), would reduce the incidence of personal bankruptcy (Danisewicz and Elard 2019). P2P funding can also be used for personal consumption, and local firms can benefit from the boost in consumer spending, thereby making it easier for them to repay their corporate loans. In these circumstances, P2P lending would increase borrowers' repayment capability and probability, at least in the short run.[3] Therefore, the growing P2P lending business would reduce banks' loan losses, leading to the expectation of a negative relation between P2P lending and commercial banks' loan losses.

However, the borrower overleveraging channel predicts a positive relation between P2P lending and banks' loan losses. An overleveraging effect might occur when borrowers have

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[2] In other words, we use loan loss provisions as a measure of loan losses. Although it would be interesting to examine the effect of P2P lending on a specific type of loan loss, we cannot directly test this effect because data on specific types of loan losses are unavailable. The available loan loss provision data aggregate a bank's loan losses from all types of outstanding loans.

[3] According to the loan purposes reported by borrowers, which are not subject to verification by the platforms, over half of the loans are used for debt consolidation or paying off credit card balance. Using funds obtained from P2P platforms to repay bank debt could be a feasible, albeit temporary, solution. However, this solution can be used strategically. For example, making a repayment allows one to borrow from the revolving account again. This could actually exacerbate borrowers' overleveraging problem because easy P2P funding helps conceal repayment problems. We discuss this issue in greater depth in the hypothesis development section.

access to P2P lending, as having overleveraged borrowers increases the incidence of nonrepayment of bank loans: “Easy money is the great cause of over-borrowing” (Fisher 1933, p. 348). It is tempting to borrow too much, especially when borrowing is easy and convenient. Banks’ existing borrowers may also borrow from P2P platforms once these platforms become available to them. In addition, facing competition from P2P platforms, banks may compromise their lending standards to issue new loans to lower-quality borrowers. Either way, as the local P2P lending market develops, banks’ individual/household borrowers would become more leveraged. The overleveraging issue caused by the P2P lending business would increase borrowers’ repayment risk. That is, the availability of easy credit via P2P lending may increase the frequency of bankruptcies by providing credit to less creditworthy borrowers, consequently leading them into a debt trap (Domowitz and Sartain 1999; Gross and Souleles 2002; White 2007; Livshits, MacGee, and Tertile 2010, 2016; Chava et al. 2019). To the extent that P2P lending leads to overleveraged borrowers, banks might suffer more loan losses. Alternatively, P2P lending and loan losses might not be related if bank managers fail to incorporate the impact of P2P lending into their loan loss provisions. In sum, it is not clear ex ante whether and how P2P lending affects banks’ loan losses.

To study the link between P2P lending and banks’ loan losses, we construct a comprehensive sample of single-state banks’ quarterly observations from 2009 to 2017. To measure each bank’s exposure to P2P lending, we extract loan-level data from the top two US P2P platforms, LendingClub and Prosper. We then aggregate the originated loan volumes by state-quarter. We test the main hypothesis by regressing loan loss provisions on the aggregate P2P lending volume for each bank’s operating state. In the regression model, we also control for a series of bank- and state-level factors, as well as bank and quarter fixed effects. Consistent with P2P lending inducing borrower overleveraging, we find that banks located in states with a higher P2P lending volume accrue for more loan losses. The positive effects are statistically and economically significant: loan loss provisions increase by 9.63 percent when P2P lending volume moves from its 25th to its 75th percentile. We also show in two-stage least squares estimation with instrumental variables based on state-level regulation that there is a positive and significant effect of P2P lending on banks' loan losses. Our main results are also robust to alternative model specifications, alternative P2P measures, and alternative samples.

Because the empirical evidence shows that the dominant effect appears to be related to the overleveraging channel, our subsequent cross-section tests and additional tests focus on confirming this channel. First, we conduct two cross-sectional tests to provide corroborative evidence for the overleveraging channel. Our first cross-sectional test exploits the variability in banks' exposure to the consumer loan market. Banks are more likely to be severely affected by P2P lending if their participation in the personal/household loan market is extensive because P2P platforms target individual/household borrowers. Consistent with this expectation, we find that the positive relation between P2P lending and loan loss provisions is stronger for banks that have a higher percentage of consumer loan balances and for banks that have a larger increase in consumer loans.

Our second cross-sectional test focuses on the ex ante leverage of consumers who borrow from banks. Consumers with higher leverage are more likely to have difficulty in repaying the banks, and other capital providers (e.g., the P2P platforms) can make these consumers even more leveraged. The effect of P2P lending on the bank's loan losses would be stronger for higher leveraged bank borrowers: once the additional funding obtained from P2P platforms is included, these borrowers are more likely to reach the default threshold. Consistent with this expectation, we find that the positive relation between P2P lending and loan loss provisions is stronger for banks that operate in states with higher household delinquency rates and for banks with a larger volume of nonperforming consumer loans.

Next, we conduct several additional tests to gain further insights on the effect of P2P lending on loan losses. First, we explore whether different components of the P2P lending volume have different effects on banks' loan losses. We divide the P2P lending volume into different components according to loan purpose (i.e., loans for debt consolidation vs. loans for other purposes) and lender type (loan volume funded by retail lenders vs. institutional lenders). We determine that our main finding is likely driven by the loans taken out for debt consolidation purpose, suggesting that individuals on the verge of default are more likely to borrow money from P2P platforms to repay their bank debt. We also find that the P2P loans funded by institutional lenders have smaller spillover effects on banks' loan losses, suggesting that institutional lenders have a higher screening ability and maintain a higher lending standard.

We also explore whether banks' capacity to make loan loss provisions moderates the relation between P2P lending and loan losses. Given that higher capacity banks are subject to fewer constraints in accruing for loan losses, we expect that the positive effects of P2P lending on loan loss provisions will be more pronounced for such banks. Consistent with our expectation, we find that the positive relation between P2P lending and loan loss provisions is stronger for banks with higher earnings before loan loss provisions and for banks with a higher regulatory capital ratio. This finding highlights the moderating role of accounting discretion.

Finally, we conduct an additional test to investigate the effect of P2P lending on bank borrowers' future actual defaults, captured by loan charge-offs. While loan loss provisions are estimated loan losses for the fiscal period, future loan charge-offs reflect the actual realized losses (i.e., confirmed defaults). Taking advantage of the natural accounting link between loan loss provisions and future charge-offs, this test validates the underlying argument of our central hypothesis and offers evidence to further support the overleveraging channel: If individuals borrowing on P2P platforms are likely to be overleveraged, then the P2P lending volume is also expected to increase future loan charge-offs, because overleveraged borrowers are more likely to default in the future. Indeed, we find a significantly positive relation between P2P lending and banks' charge-offs in the next quarter.

This study makes two contributions to the literature. First, we add to the growing FinTech literature. As noted earlier, extant literature in this area typically investigates how fund providers evaluate borrowers (e.g., Michels 2012; Duarte et al. 2012; Zhang and Liu 2012; Lin et al. 2013) and how the P2P lending market works (e.g., Wei and Lin 2017; Vallee and Zeng 2019; Du et al. 2019). More recent studies investigate the interaction between P2P lending platforms and the traditional banking system (e.g., Butler et al. 2017; Cornaggia et al. 2018; Tang 2019; Chava et al. 2019). Through the lens of P2P lending, we study the spillover effects of FinTech development on traditional financial institutions. To the best of our knowledge, we are the first to link P2P lending with traditional banks' loan losses via the overleveraging channel.

Second, this paper contributes to the literature on loan loss provisions. This broad literature studies the factors that bank managers take into consideration or those that affect managerial discretion in the estimation of loan loss provisions (e.g., Ahmed, Takeda, and Thomas 1999; Liu and Ryan 2006; Beatty and Liao 2011, 2014; Bushman and Williams 2012, 2015; Bouvatier and Lepetit 2012; Beck and Narayanamoorthy 2013; Andries, Gallemore, and Jacob 2017; Hribar, Melessa, Small, and Wilde 2017; Dou, Ryan, and Zou 2018; Nicoletti 2018). We document evidence suggesting that given the rapid development of the P2P lending business, banks' P2P lending exposure has become an important factor in determining the level of loan loss provisions in recent years. By documenting an adverse impact of P2P lending on commercial banks, our study may also have policy and regulatory implications.

The rest of this paper is organized as follows. Section II introduces the background and develops the hypotheses. Section III describes the data and research design. The main findings and robustness tests are reported in Section IV. Section V discusses the cross-sectional analyses. Additional analyses are provided in Section VI before conclusions are drawn in Section VII.

II. BACKGROUND AND HYPOTHESES DEVELOPMENT

The P2P Lending Business

P2P lending is the implementation of crowdfunding in the household finance arena, and it represents one of the most important segments of the FinTech industry.[4] P2P lending relies on online platforms and mainly focuses on the unsecured personal loan market. As with credit cards, borrowing money on P2P platforms does not require collateral. P2P lending is both more convenient and more efficient than traditional bank lending because the loan origination process is largely automated via the platform's preset algorithm, whereas the traditional process requires intensive human effort. P2P platforms act like a bank but are not actually banks in that they do not bear the credit risk. Rather, they are essentially an agent linking individuals who need to borrow and those who are willing to lend. Under the P2P lending business model, the platform serves as an information provider; that is, it collects loan applicants' information and passes it on to potential investors. Investors then make their own decision (about whether or not to lend money to the loan applicants) based on the information provided. The investors also bear all the credit risk; that is, they bear the loss if the borrower defaults.

An individual who wants to borrow money on P2P lending platforms can register as a borrower and submit an application online. Along with the loan description, the borrower is required to report certain key information, such as employment status, annual income,

[4] Other segments of the FinTech industry include digital payment, crowdfunding for small businesses, robo-advising, and so forth.

property ownership, loan purpose, loan term, and loan amount. The platform then screens the loan application via a proprietary algorithm. P2P lending platforms evaluate the application and the borrower's credit report from a credit bureau.[5] Owing to advanced computer technology, this evaluation process takes only a few seconds before the applicant receives various loan options for which the applicant qualifies, including the loan term, loan amount, and interest rate. After the applicant selects an option and completes the application process, platforms such as LendingClub may ask for and review some supporting documents (e.g., to verify the borrower's reported annual income level). Once this verification is complete, the loan is listed on the platform to attract investor commitments. When investor commitments reach a certain level, the applicant receives the loan from the issuing bank acting as the lending platform's business partner in the P2P loan origination process. Shortly after the loan is issued, the P2P lending platform uses the proceeds from investors to purchase the loan from the issuing bank. Finally, the platform issues new securities (e.g., borrower payment-dependent notes) to the investors who committed to funding the loan. Figure 1 depicts the loan issuance mechanism of P2P lending platforms. Over the life of the loan, borrowers are required to make repayments to their investors via the platform, which serves as a monitor after a loan is originated. P2P platforms will pursue delinquent borrowers for overdue debt and they regularly report delinquent borrowers to credit bureaus.[6] Borrowers have to pay origination fees charged by P2P platforms upon loan origination. P2P platforms may also charge late fees and other penalties when borrowers fail to make their scheduled repayments.

[Insert Figure 1 Here]

Since the establishment of the first P2P lending platform, Prosper Marketplace, in 2006,

[5] Checking credit information on behalf of borrowers generates a soft credit inquiry, which is visible only to the borrowers themselves. A hard credit inquiry, which may affect a borrower' credit score, only appears when the P2P loan is issued.

[6] For example, see LendingClub's frequently asked questions: What to expect when a loan is late. https://help.lendingclub.com/hc/en-us/articles/216127917-What-to-expect-when-a-loan-is-late-.

other platforms have emerged in the market, including LendingClub, Upstart, Funding Circle, and SoFi, among others. As a result, the P2P lending market is developing rapidly and attracting significant attention from both the media and academia. According to statistics from TransUnion, a US consumer credit reporting agency, US FinTech firms helped the unsecured personal loan market hit an all-time record high of $138 billion in 2018, with the market share of FinTech companies reaching 38 percent that year from just 5 percent in 2013.[7] The US P2P lending market is highly concentrated and the two largest players are LendingClub and Prosper. In 2014, for example, LendingClub and Prosper issued approximately $4.6 and $1.6 billion worth of new loans, respectively, and they represent 64 percent and 22 percent of the US P2P lending market.[8] These two platforms are also the top two platforms worldwide.[9]

P2P Lending and Banks' Loan Losses

The interaction between FinTech firms and traditional financial intermediaries is an important and interesting research topic. This interaction may not only affect both parties' individual development but also have a substantial impact on the financial system as a whole. Although P2P lending platforms and traditional banks have different business models, they serve nearly identical functions as far as potential borrowers, particularly individuals and households, are concerned. One stream of the literature focuses on these intermediaries' customer bases and investigates whether P2P lending substitutes for or complements bank lending (e.g., Tang 2019; Cornaggia et al. 2018). Complementing this line of literature, we focus on the spillover effects of P2P lending on banks' loan losses. We argue that the relation

[7] See CNBC news article published on February 21, 2019: "Fintechs help boost US personal loan surge to a record $138 billion". https://www.cnbc.com/2019/02/21/personal-loans-surge-to-a-record-138-billion-in-us-as-fintechs-lead-new-lending-charge.html.

[8] See MEDICI's online report "US peer-to-peer (P2P) lending market: A sector snapshot" (November 13, 2015). https://gomedici.com/us-peer-to-peer-p2p-lending-market-a-crisp-report.

[9] See Statista for the statistics: https://www.statista.com/statistics/468469/market-share-of-lending-companies-by-loans/.

between P2P lending and banks' loan losses is an empirical question.

The bank loan repayment channel predicts a negative relation between P2P lending and banks' loan losses. Individual/household borrowers may directly use the funding obtained from P2P platforms to repay their bank debt. In fact, the statistics of loan purposes show that debt consolidation is the most common reason borrowers give when they apply for a loan on a P2P lending platform.[10] Using P2P funding for debt consolidation is reasonable, especially when banks charge a higher interest rate. P2P funding could also reasonably be used to manage a short-term gap in cash flow. For example, the easy funding available on a P2P platform may provide a temporary solution to repaying a mortgage loan secured by the borrower's home, as no one wants to lose his or her home due to a short-term cash flow problem. Accordingly, banks may well think of the additional funding available from P2P lending platforms as arguably increasing borrowers' ability to repay their bank loans and reducing the incidence of personal bankruptcy (Danisewicz and Elard 2019). Accordingly, when borrowers can easily borrow money on P2P platforms, bank managers might expect a lower default risk and thus accrue for less loan losses.

Furthermore, the development of P2P lending can also indirectly facilitate local firms' repayment of their corporate loans. Besides consolidating debt and paying off credit card balances, loans are also used for personal consumption, such as large purchases, medical expenses, and home improvement. Given the ease of applying for P2P loans, this additional funding source is likely to boost consumer spending. Positive government spending shocks can stimulate the local economy (e.g., Blanchard and Perotti 2002). Similarly, local firms can benefit from the boost in consumer spending. They may achieve higher profitability and cash flow, which in turn will increase their debt capacity and decrease their default risk. Taken together, easy funding from P2P lending platforms can directly enhance individual/household

[10] It is worth noting that loan purposes are self-reported by borrowers and are not actually verified by P2P platforms. Detailed statistics of loan purposes can be found in Figure 5.

borrowers' repayment flexibility and/or indirectly expand corporate borrowers' repayment capacity, resulting in less loan losses for local commercial banks.[11]

However, the borrower overleveraging channel predicts a positive relation between P2P lending and banks' loan losses. First of all, banks' existing borrowers may seek additional loans from P2P platforms once these platforms become available to them. Credit expansion resulting from P2P lending occurs among borrowers who already have access to bank credit (Tang 2019). Furthermore, it is tempting to borrow too much, especially when FinTech development has made borrowing easier and more convenient. To the extent that those already borrowing from commercial banks are inclined to borrow more, they could easily increase their debt level by tapping the additional funding sources available on P2P lending platforms. Such borrowers could potentially run into the overleveraging problem and eventually personal bankruptcy (Fisher 1933; Domowitz and Sartain 1999; Gross and Souleles 2002; White 2007; Livshits et al. 2010, 2016; Chava et al. 2019). In that case, banks are expected to suffer more loan losses.

Under the aforementioned overleveraging effect of P2P lending on banks' existing borrowers, we implicitly assume that banks face a challenge in dealing with such borrowers. Several reasons support this assumption. First, banks may have difficulty identifying borrowers who ex ante want to borrow more. Second, it might be too costly for banks to stop serving existing borrowers even though they will probably become more leveraged if they also borrow on P2P platforms. Third, banks may be aware of the overleveraging issue, but they probably cannot prevent such borrowers from seeking further loans on P2P platforms.[12] It is worth noting that this overleveraging effect of P2P lending on banks' existing borrowers

[11] To the extent that P2P lending platforms and bank lending complement each other and respectively serve lower-quality and higher-quality borrowers, one might also expect a negative relation between P2P lending and loan losses because the lower quality borrowers of banks may migrate to P2P platforms.

[12] Unlike corporate loans, consumer loans (including credit cards) are unsecured and their amounts are smaller; hence they are costly to monitor after origination.

is not restricted to the unsecured personal loan market even though the P2P lending platforms are aimed at this niche market. Instead, the effect also applies to banks' general individual/household borrowers, regardless of the loan purpose and collateral condition. For example, overleveraging due to excessive consumer loans from P2P lending platforms can reduce borrowers' ability to repay their bank mortgage loans.

P2P lending may contribute to borrowers' overleveraging problem in another way. As discussed earlier, borrowers may use P2P funding to repay their bank debt and credit card balances. In this case, P2P borrowing would not affect the borrowers' overall debt level. However, if after repaying the bank, borrowers again borrow money from the bank, particularly through revolving accounts such as credit cards, then P2P lending will contribute to overleveraging. Chava et al. (2019) document that P2P borrowers' credit card balances decline dramatically immediately after the P2P loan origination. More importantly, these authors also find that the credit card balances quickly revert to their earlier level and the borrowers then become even more highly leveraged because they now have to pay off loans from both the bank and the P2P platform. In such cases, borrowers are likely to fall into a vicious cycle of an overleveraging problem exacerbated by the availability of P2P funding sources. Easy funding from a P2P platform might be the last resort for borrowers on the verge of default. Taken together, even though the P2P funding might be used to repay bank debt, borrowers on P2P platforms can eventually become overleveraged.

In addition, banks may compete with P2P platforms and issue new loans to lower quality borrowers. Prior studies suggest that P2P platforms directly compete with commercial banks (Cornaggia et al. 2018; Tang 2019). For example, Cornaggia et al. (2018) show that banks, especially the smaller ones, are losing a portion of the personal loan market to P2P lending platforms. Tang (2019) shows that lower-quality bank borrowers are likely to migrate to a P2P platform when banks tighten their lending standards, which suggests that P2P lending substitutes for bank lending in terms of serving infra-marginal bank borrowers. Facing competition from P2P lending platforms, banks are expected to lower their lending standards to maintain or even expand their market share (Ruckes 2004; Dick and Lehnert 2010). Competition imposes downward pressure on bank profits and thus reduces charter value, which in turn creates incentives for excessive bank risk-taking (Keeley 1990; Bushman, Hendricks, and Williams 2016).[13] Specifically, banks may issue new loans to extant borrowers who are already overleveraged. Alternatively, they may reach out to potential borrowers of lower quality. It is worth noting that the direct competition argument is only relevant to the unsecured personal loan market where P2P lending platforms and traditional banks go head to head.

In summary, banks' existing borrowers may also take out loans from P2P platforms, and banks may also compete with P2P platforms to issue new loans to lower-quality borrowers. Either way, banks' individual/household borrowers will become more leveraged. This borrower overleveraging channel predicts a positive relation between P2P lending and banks' loan losses. While the bank loan repayment channel predicts the opposite and creates tension with this hypothesis, prior literature shows that borrowers can eventually become overleveraged even though they use the borrowed P2P funding to repay their bank debt. All in all, we predict that banks will suffer more loan losses as the local P2P lending market becomes more developed. We state this hypothesis below in alternative form. Figure 2 summarizes the relevant arguments and counter-arguments.

H1: Banks that operate in states with a higher P2P lending volume will suffer more loan losses.

[Insert Figure 2 Here]

Cross-Sectional Variation in the Effects of P2P Lending on Banks' Loan Losses

[13] Not all studies find this result. See Boyd and De Nicoló (2005) and Akins, Li, Ng, and Rusticus (2016) for an alternative point of view.

Next, we explore several conditions that likely increase the impact of P2P lending on banks' loan losses. A key objective of these cross-sectional analyses is to provide corroborative evidence for the borrower overleveraging channel through which P2P lending can increase banks' loan losses.

First, we focus on a bank's exposure to the consumer loan market. P2P lending platforms target individual and household borrowers, so these types of borrowers from banks are likely to be affected by P2P lending. In keeping with the overleveraging effect of P2P lending on banks' existing borrowers, banks that are more exposed to the individual/household loan market are likely to be more severely affected by P2P lending. Banks can also expose themselves more to the consumer loan market by aggressively competing with P2P platforms. Price aggressiveness and risk-taking are common competition strategies (Churchill, Ford, and Ozanne 1970; Thomas 1999; Yamawaki 2002; Simon 2005; Ruckes 2004; Dick and Lehnert 2010; Bushman et al. 2016). Banks that are more aggressive in pricing or more willing to take risk are likely to issue more new loans to lower-quality borrowers. Consequently, these banks are also likely to experience more loan losses. Taking this evidence together, we expect the positive association between P2P lending and loan losses to be stronger for banks with greater exposure to the consumer loan market. We state this hypothesis as follows:

H2: The effect of P2P lending on banks' loan losses will be stronger for banks that have greater exposure to the consumer loan market.

Second, we focus on the ex ante leverage of consumers who borrow money from banks. Consumers with higher leverage are more likely to have difficulty repaying their bank debt, and the competitors (i.e., the P2P platforms) can make these consumers even more leveraged. When bank borrowers already have relatively high leverage, the additional loans obtained from P2P platforms increase the borrowers' debt and make them more likely to reach the default threshold. In contrast, the additional funding from P2P lending platforms may not contribute much, if anything, to the overleveraging problem if a bank's borrowers have relatively low leverage because they are probably still capable of repaying the increased level of debt. Accordingly, we expect the positive association between P2P lending and banks' loan losses to be stronger for banks whose consumer borrowers are more highly leveraged. We state this hypothesis as follows:

H3: The effect of P2P lending on banks' loan losses will be stronger for banks whose consumer borrowers have a higher leverage.

III. DATA AND RESEARCH DESIGN

Data, Sample, and Variable Construction

This study relies on two major data sources, P2P lending data and bank data, along with supplementary datasets. To measure P2P lending intensity, we retrieve detailed loan-level data from the top two P2P lending platforms in the United States, LendingClub and Prosper.[14] LendingClub started in 2007 and went public in 2014. It is now the market leader, having originated loans amounting to $50 billion as of June 2019. Prosper is America's first P2P lending marketplace (established in 2006). As of June 2019, it has funded $15 billion in loans. These two platforms' loan-level datasets contain comprehensive information such as borrower location, loan origination date, loan amount, loan purpose, and so forth. To avoid confounding effects during the recent economic recession, defined by NBER as 2007Q4-2009Q2, our sample period starts in 2009Q3 and ends in 2017Q4. Figures 3A and 3B present the quarterly loan origination volume at LendingClub and Prosper, respectively. Prior to the 2016 P2P lending crisis, both platforms saw rapid growth in loan origination.[15] Consistent with Balyuk and Davydenko's (2019) observation, loan volume recovered quickly after the

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[14] LendingClub provides summary statistics and makes historical loan-level data (from 2007 to the present) available for download at its official website: https://www.lendingclub.com/info/statistics.action. Prosper data are available for download at https://www.prosper.com/investor/marketplace#/download.

[15] The crisis was triggered by two separate events: the LendingClub scandal and Moody's downgrade warning on the securitization of Prosper loans.

temporary drop sparked by the P2P crisis.

To link the P2P lending data to each commercial bank, we aggregate P2P lending volume at the state-quarter level and then match it with bank-quarter observations through the bank operating footprint. The reason for a state-level aggregation is that P2P lending platforms are governed by state securities regulators. P2P lenders such as LendingClub must obtain a state license before they can begin lending in the state.[16] Regulators impose restrictions on both borrowers and investors, making it impossible for participants to borrow or invest money via a P2P platform if the platform does not hold a license in their state of residence (Cornaggia et al. 2018). This state-level regulation and the timing difference in obtaining the state licenses creates significant cross-sectional variation in P2P lending volumes. Figures 4A and 4B present the geographic distribution of the loan origination volume at LendingClub and Prosper, respectively. For example, over the sample period, LendingClub did not operate in Iowa, while it did in two neighboring states, Illinois and Missouri, with accumulated loan volumes of $1,087 and $403 million, respectively.

Specifically, we aggregate the loan amount by state (based on borrower location) and quarter (based on loan origination date). For each state-quarter, we first obtain the raw value of the aggregate P2P lending volume, which includes all loans originated through LendingClub and Prosper in the quarter and the state. To capture banks' P2P lending exposure, we define the main P2P measure ($LNP2P_{s,t-1}$) as the natural logarithm of 1 plus the aggregate P2P loan origination volume during quarter $t-1$.[17]

To provide some stylized facts, we also aggregate the loan volume according to other classifications. First, we classify the total loan volume during the whole sample period by

[16] For example, a list of LendingClub's state licenses is available at https://www.lendingclub.com/legal/licenses.

[17] As a robustness check, we also define a scaled P2P measure as the raw value of the aggregate P2P lending volume scaled by the state population and find qualitatively similar results. The state population is arguably an appropriate scalar because in the early years of the sample period, both the demand and supply of P2P funding came mainly from individuals. Hence a state with a larger population is naturally expected to generate a larger P2P lending volume. The results are reported in Table 3.

loan purpose as reported by the borrowers themselves.[18] As shown in Figure 5, the most common purpose for P2P funding is debt consolidation and credit card repayment. Other common reasons include home improvement, large purchases, and medical expenses. Second, we divide all individual loans in our sample according to their listing status, which identifies their investor type. Basically, only individual investors could invest in P2P loans prior 2013. In 2013, both LendingClub and Prosper began separating their investors into two pools: a fractional pool and a whole pool. While individual investors can only provide funding to the fractional pool, institutional investors can only lend money to the whole pool.[19] As shown in Figure 6, institutional investors on both platforms now dominate supply-side funding.

[Insert Figures 3, 4, 5, and 6 Here]

Our study focuses on US commercial banks. We extract bank-level data from call reports filed with bank regulators.[20] Call reports contain quarterly financial data for each US bank, which we use to construct a series of bank-level variables. Our identification strategy exploits the variation in P2P lending across states that is primarily driven by state-level regulation. Borrowers are not allowed to apply for a P2P loan unless the lending platform has obtained a license in their state of residence. Therefore, to sharpen our analyses, we restrict our sample to single-state banks (i.e., banks that operate geographically within the borders of a specific state).[21] To identify single-state banks, we rely on the FDIC's Summary of Deposits (SOD) database. The SOD database contains the results of the annual survey of branch office

[18] Loan purpose describes the borrowers' reported intent; it may not reflect actual usage.

[19] For example, the mechanics of LendingClub are as follows: loans that meet the listing criteria will be randomly allocated at the grade and term level either to a program designed for retail investors who would prefer to buy a fraction of a loan or to a program intended for institutional investors who can buy the loan in its entirety. For details on how LendingClub works with different types of investors, visit https://help.lendingclub.com/hc/en-us/articles/115009000328-How-LendingClub-balances-different-investors-on-its-platform.

[20] Call report data for US commercial banks are publicly available online at the Federal Reserve Bank of Chicago: https://www.chicagofed.org/banking/financial-institution-reports/commercial-bank-data.

[21] As a robustness check, we show that including banks operating in more than one state in our sample does not change our inference. Specifically, we calculate the weighted average P2P lending exposure for multistate banks following Akins et al. (2016), in which the weighting scheme is based on the geographical distribution of bank deposits.

deposits as of June 30 for all FDIC-insured institutions. Specifically, we classify a bank as a single-state bank if all of its deposits are from branches located in the same state. We also utilize the SOD data to construct a competition measure of the banking industry at the state level.

Finally, we merge the P2P lending data with bank data and complement the merged dataset with various state-level macroeconomic control variables. After dropping observations with missing values for the regression variables, we obtain our final sample which consists of 201,056 bank-quarter observations of 7,325 unique banks. In a nutshell, the final sample covers all available single-state banks' quarterly data during the period from 2009Q3 to 2017Q4.

Empirical Model

We use the following OLS model to examine the relation between P2P lending and banks' loan losses:

$$\begin{aligned} LLP_{i,t} = {} & \beta_0 + \beta_1 LNP2P_{s,t-1} + \beta_2 SIZE_{i,t-1} + \beta_3 EBP_{i,t} + \beta_4 CAPR1_{i,t-1} + \beta_5 ALW_{i,t-1} \\ & + \beta_6 HHI_{i,t-1} + \beta_7 HETE_{i,t-1} + \beta_8 \Delta LOAN_{i,t} + \beta_9 \Delta GDP_{i,t} + \beta_{10} \Delta UNEMP_{i,t} \\ & + \beta_{11} \Delta HPI_{i,t} + \beta_{12} \Delta POP_{i,t} + \beta_{13} GDP_{i,t-1} + \beta_{14} UNEMP_{i,t-1} + \beta_{15} HPI_{i,t-1} \\ & + \beta_{16} POP_{i,t-1} + \beta_{17} AUTOD_{i,t-1} + \beta_{18} CCD_{i,t-1} + \beta_{19} MORTD_{i,t-1} \\ & + \beta_{20} DELINQ_{i,t-1} + bank\ fixed\ effects + quarter\ fixed\ effects \\ & + \varepsilon_{i,t}. \end{aligned} \tag{1}$$

In Equation (1), the unit of analysis is the bank-quarter observation. We use loan loss provisions reported in income statements to measure banks' loan losses. Specifically, the dependent variable ($LLP_{i,t}$) is bank *i*'s loan loss provisions in quarter *t*, scaled by its lagged total outstanding loans. The variable of interest is the P2P lending variable ($LNP2P_{s,t-1}$), defined as the natural logarithm of 1 plus the P2P lending volume (in billion US dollars) aggregated by the state-quarter.[22] As described in the previous section, this variable measures the P2P lending exposure of banks operating in state s in quarter $t-1$. Therefore, our focus is the regression coefficient on $LNP2P_{s,t-1}$ (i.e., β_1). In our central hypothesis, we argue that P2P lending could induce bank borrowers' overleveraging problem, thus resulting in a higher repayment risk. Thus, we expect β_1 to be significantly positive.

Following the prior loan loss provisioning literature (e.g., Beatty and Liao 2011, 2014; Bushman and Williams 2012, 2015; Bushman et al. 2016; Hribar et al. 2017; Dou et al. 2018), we include a series of bank-level control variables.[23] First, we control for lagged bank size ($SIZE_{i,t-1}$), which is a common control variable in the accounting and finance literature. The banking literature also controls for bank size because it is a commonly used threshold for closer regulatory scrutiny. To address earnings management and regulatory capital management incentives, we control for earnings before loan loss provisions ($EBP_{i,t}$) and the lagged tier 1 risk-based capital ratio ($CAPR1_{i,t-1}$). In banks' credit loss accounting, loan loss provisions are accrued quarterly and accumulated in a balance sheet account, namely loan loss reserves/allowances. More importantly, the amount of loan loss provisions to be made in the current quarter depends on the amount accumulated in past quarters. Therefore, we also control for lagged loan loss allowances ($ALW_{i,t-1}$). Finally, we control for banking industry competition ($HHI_{i,t-1}$), loan heterogeneity ($HETE_{i,t-1}$) and loan growth rate ($\Delta LOAN_{i,t}$), all of which are important determinants of loan loss provisions as prior studies have shown.

Because our identification strategy relies on the variation in P2P lending across states and quarters, we need to control for state-quarter-level macroeconomic variables that may

[22] We take the natural logarithm rather than scale aggregate lending volume to be consistent with most other studies on P2P lending. We include state-level controls and bank fixed effects (which subsume state fixed effects), so the difference in size across states is already controlled for. In Table 3 we show that the results are robust to various scaled measures of P2P lending.

[23] To avoid the over-controlling problem, in the baseline regression model, we do not control for variables related to nonperforming loans and charge-offs because these variables are potential outcome variables. Nevertheless, we conduct robustness checks to further control for these variables and our results still hold. See Table 3 for details.

affect banks' loan loss provisions and P2P lending activities. We address this issue by including a variety of state-level variables. First, we control for several macroeconomic indicators commonly used in the banking literature, including the level of and the change in state-level GDP per capita ($GDP_{s,t-1}$, $\Delta GDP_{s,t}$), the state unemployment rate ($UNEMP_{s,t-1}$, $\Delta UNEMP_{s,t}$), the house price index ($HPI_{s,t-1}$, $\Delta HPI_{s,t}$), and the state population ($POP_{s,t-1}$, $\Delta POP_{s,t}$). Second and more specific to the P2P lending setting, we follow Butler et al. (2017) and Cornaggia et al. (2018) to control for the household debt level and credit quality. Specifically, we control for three types of household debt and the overall household debt delinquency rate: auto debt ($AUTOD_{s,t-1}$), credit card debt ($CCD_{s,t-1}$), and home mortgage debt ($MORTD_{s,t-1}$), as well as the overall delinquency rates ($DELINQ_{s,t-1}$), which are defined as the percentage of household debt that is 90 days or more delinquent.

We summarize the variable definitions in Appendix A. To reduce the influence of outliers, all continuous variables are winsorized at the 1 and 99 percent levels of their respective distributions. Finally, we include bank and year-quarter fixed effects. Bank fixed effects are included to control for unobserved time-invariant bank characteristics that influence loan loss provisions. Including year-quarter fixed effects allows us to control for nationwide time-variant economic conditions. We use robust standard errors two-way clustered by bank and quarter to address the issue of heteroscedasticity and cross-sectional and serial correlation in the error terms (Petersen 2009; Gow et al. 2010).

Descriptive Statistics

Table 1 presents the mean, standard deviation, median, and the 25th and 75th percentile values of the variables used in our main regression. Our final sample covers all available single-state banks for the period from 2009Q3 to 2017Q4, consisting of 201,056 bank-quarter observations. The mean (median) value of loan loss provisions ($LLP_{i,t}$) in our sample is 0.12 percent (0.04 percent) of the lagged outstanding loans. Consistent with recent studies such as

Hribar et al. (2017), over 25 percent of the bank-quarter observations involve zero loan loss provisions. As for the P2P lending volume variable ($LNP2P_{s,t-1}$), defined as the natural logarithm of 1 plus the P2P lending volume (in billion US dollars) aggregated by the state-quarter, the mean (median) value is 0.0258 (0.0060). Statistics for the other bank-level and state-level variables are largely consistent with prior literature (e.g., Butler et al. 2017; Hribar et al. 2017; Dou et al. 2018; Cornaggia et al. 2018).

[Insert Table 1 Here]

IV. EMPIRICAL RESULTS

P2P Lending and Banks' Loan Losses

In this section, we test our central hypothesis (H1). From bank borrowers' perspective, P2P lending platforms provide another source of funding that is relatively easy and convenient to obtain. We argue that, on the one hand, this easy funding source could help borrowers repay their bank debt, thus reducing banks' loan losses. On the other hand, P2P lending can lead to borrowers' overleveraging, thereby increasing the repayment risk. Moreover, easy money from a P2P lending platform could represent a short-term solution for borrowers who are about to default. Borrowers who repay bank debt using money borrowed on a P2P platform may be overleveraged. Therefore, we posit that bank managers would report more loan losses in response to an increase in P2P lending activities. Table 2 presents the results of testing H1 via the estimation of Equation (1). In this baseline model, we regress loan loss provisions ($LLP_{i,t}$) on the P2P lending measure ($LNP2P_{s,t-1}$) and several control variables. In Table 2 and all remaining tables, bank and quarter fixed effects are included and standard errors are two-way clustered by bank and quarter; the constant terms are estimated but omitted from the presentation.

We start our analyses with a simplified model that does not control for any bank-level variables in column (1) and then estimate the baseline model in column (2). As Table 2 shows, the regression coefficients on $LNP2P_{s,t-1}$ are significantly positive in both columns and of similar magnitudes. Our baseline results in column (2) show that the coefficient on $LNP2P_{s,t-1}$ is 0.0040, which is statistically significant at the 1 percent level (t-value = 5.40). This finding supports the prediction that banks operating in a state with a higher P2P lending volume report more loan losses, indicating that banks suffer from overleveraged borrowers. Moreover, the magnitude of the regression coefficient is economically significant. Loan loss provisions increase by 9.63 percent when $LNP2P_{s,t-1}$ moves from its 25th to its 75th percentile.[24] Given that the P2P lending market is still growing steadily, this magnitude is considerable.[25]

The regression results on the control variables are largely consistent with both prior literature and intuition. For example, the coefficient on bank size ($SIZE_{i,t-1}$) is significantly positive while that on earnings before provisions ($EBP_{i,t}$) is significantly negative, which is consistent with the recent literature (e.g., Bushman et al. 2016; Hribar et al. 2017; Dou et al. 2018). In terms of macro-level variables, the state unemployment rate ($UNEMP_{s,t-1}$, $\Delta UNEMP_{s,t}$) is positively associated with loan loss provisions. Meanwhile, the house price index ($HPI_{s,t-1}$, $\Delta HPI_{s,t}$) is negatively associated with loan loss provisions. Consistent with the notion that a higher debt level is associated with a higher repayment risk, the coefficients on all three types of household debt—auto debt ($AUTOD_{s,t-1}$), credit card debt ($CCD_{s,t-1}$), and home mortgage debt ($MORTD_{s,t-1}$)—are all significantly positive.[26]

[Insert Table 2 Here]

[24] The reported percentages are calculated based on the estimated coefficient and the distribution of the independent and dependent variables using the following formula: [regression coefficient × (75th percentile − 25th percentile of the independent variable)]/the mean value of the dependent variable. For example, in column (1) of Table 3, [0.0040 × (0.0297 − 0.0008)]/0.0012 = 9.63%.

[25] The global P2P lending market is expected to expand at a CAGR of 50.2% during the forecast period from 2019 to 2025. See https://brandessenceresearch.biz/ICT-and-Media/Peer-to-Peer-(P2P)-Lending-Market-Share/Summary.

[26] Because macroeconomic variables are probably correlated with each other and including them in the model could result in a multicollinearity problem, we check the variance inflation factor (VIF) after running the baseline model. We find that no individual VIF exceeds or even approaches the rule of thumb of 10.

Robustness Checks

In this section, we conduct robustness checks to evaluate whether our baseline results are sensitive to additional control variables, alternative P2P lending measures, and several alternative samples. Results are reported in Table 3.

In our baseline model, we do not control for variables related to loan charge-offs and nonperforming loans. Our study differs from prior literature that aims to derive abnormal loan loss provisions. Instead, the purpose of our study is to investigate whether and how P2P lending affects banks' loan losses. In addition, including variables related to loan charge-offs and nonperforming loans may result in the over-controlling problem because these variables are potential outcomes of increased P2P lending. Nevertheless, we check whether our results are sensitive to these additional control variables. First, we follow Kanagaretnam et al. (2010) to further control for beginning nonperforming loans ($NPL_{i,t-1}$), current net charge-offs ($CO_{i,t}$), and the change in nonperforming loans ($\Delta NPL_{i,t}$). Second, we follow the suggestion of Basu et al. (2020) to account for asymmetric loan loss provisioning. That is, in addition to controlling for current net charge-offs ($CO_{i,t}$) and a series of changes in nonperforming loans ($\Delta NPL_{i,t}$, $\Delta NPL_{i,t-1}$, and $\Delta NPL_{i,t-2}$), an indicator for a decrease in nonperforming loans ($D\Delta NPL_{i,t}$) and an interaction term ($D\Delta NPL_{i,t} \times \Delta NPL_{i,t}$) are also included in the model. Columns (1) and (2) of Table 3 show that the coefficients on $LNP2P_{s,t-1}$ are significantly positive, with t-values of 5.02 and 5.24, respectively.

Next, we check whether our results are sensitive to several alternative P2P measures. In our baseline regression, we have used the main P2P measure, which is defined as the natural logarithm of 1 plus the aggregate P2P loan origination volume during quarter $t-1$. As robustness checks, we propose three alternative P2P measures. First, we define a scaled P2P measure ($P2PPOP_{s,t-1}$) as the raw value of the aggregate P2P lending volume scaled by the state population, which is arguably a reasonable scalar given that P2P platforms target individual borrowers. Besides P2P lending volume, which is a flow measure, we also consider using P2P lending balance which is a stock measure. The balance-based P2P measure ($P2PBAL_{s,t-1}$) is defined as the aggregate P2P loan balance scaled by the state population. The third alternative measure ($P2PNPL_{s,t-1}$) is defined as the percentage of nonperforming P2P loans divided by the total outstanding P2P loans.[27] The third measure has closer ties to the spillover effects than the first two measures: P2P loan repayment problems can create problems for bank loans. As shown in columns (3)-(5) of Table 3, with a focus on these alternative P2P measures, we continue to find a significantly positive relation between P2P lending and banks' loan losses.

We also check whether our results are driven by observations from a particular state. For example, neither LendingClub nor Prosper had lending activities in the state of Iowa throughout our sample period (2009Q3-2017Q4). Meanwhile, both lending platforms were most active, in terms of lending activities, in the state of California, which is also the headquarters state for the two platforms as well as many other innovative high-tech firms. These two states may each have unique features that could affect both the P2P lending platforms and the banking industry. To address this issue, we exclude Iowa and California from columns (6) and (7) of Table 3, respectively. After removing these states from our sample, we continue to find a significant coefficient on $LNP2P_{s,t-1}$. Therefore, our results are unlikely to be driven by particular states.

In addition, we conduct another robustness check in which we take into account multistate banks. To accurately measure banks' P2P lending exposure at the state level, we restrict our sample in the baseline analysis to single-state banks. However, excluding multistate banks, which are typically larger in size, may decrease the generalizability of our main finding. Because P2P lending volume is measured at the state level, we need a

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[27] To construct the last two alternative measures ($P2PBAL_{s,t-1}$ and $P2PNPL_{s,t-1}$), we need detailed repayment data, which are only available for LendingClub.

weighting scheme to measure multistate banks' P2P lending exposure. Taking the approach introduced in prior research, such as Akins et al. (2016), and using the weighting scheme based on the geographical distribution of bank deposits, we calculate the weighted average P2P lending exposure for multistate banks. In the same vein, all state-level control variables for multistate banks are calculated as the weighted average value. Finally, we obtain a bigger sample by adding multistate banks to the original single-state bank sample. The sample size increases from 201,056 to 221,854. Column (8) of Table 3 presents the regression results for this bigger sample. Again, we continue to find a significantly positive relation between P2P lending and banks' loan losses. Specifically, the regression coefficient on $LNP2P_{s,t-1}$ is 0.0039, which is statistically significant at the 1 percent level (t-value = 5.72). Therefore, our baseline results are robust to this alternative sample that includes multistate banks.

Finally, we also check whether our results are affected by banks involved in mergers and acquisitions. Following Beatty and Liao's (2011) approach, we exclude all observations with a quarterly growth rate of non-loan assets exceeding 10 percent. This exclusion significantly reduces our sample size from 201,056 to 165,121. However, the regression results are very similar to our baseline results: in column (9) of Table 3, the coefficient on $LNP2P_{s,t-1}$ is significantly positive (coeff. = 0.0041, t-value = 5.48). Taken together, the findings in Table 3 show that our results are robust to additional control variables, alternative P2P lending measures, and alternative samples.

[Insert Table 3 Here]

Instrumental Variable Approach to Address Endogeneity Concerns

An important driver of variation in P2P lending volume is state-level regulation, since P2P platforms must obtain a license for a particular state before they can operate in that state. This driver is outside the influence of individual borrowers or commercial banks. Therefore, endogeneity concerns are already somewhat mitigated even in our baseline specification, especially given the inclusion of a series of state-level controls, bank fixed effects, and year-quarter fixed effects. Nonetheless, our research design may not have adequately controlled for factors that influence both P2P lending activities and banks' loan loss provisions.

In this section, we take the instrumental variable (IV) approach to address endogeneity concerns by isolating the effect of differences in state-level regulation. Under the current business model, as depicted in Figure 1, P2P lending business is subject to both federal and state-level regulations. Specifically, LendingClub and Prosper must obtain a state-level license to operate a lending business in a particular state. Primarily due to this license requirement, LendingClub and Prosper started operating in some states later than in others. We exploit this variation in when licenses were obtained to construct instrumental variables. It is not immediately apparent that license application and approval are correlated with the conditions of the banking industry. However, the status and history of the state-level license obviously have a significant impact on the P2P lending volume within that state.

We obtain the state-level license status from the 10-Ks that LendingClub and Prosper filed with the Securities and Exchange Commission (SEC). For example, in the 10-K filing for the fiscal year ended March 31, 2010, LendingClub states that "LendingClub is a licensed lender or loan broker in a number of states and…, with the exceptions of Idaho, Indiana, Iowa, Kansas, Maine, Mississippi, Nebraska, North Carolina, North Dakota and Tennessee." In the 10-K filing for the next fiscal year ended March 31, 2011, LendingClub states "We hold licenses in a number of states and…, with the exceptions of Idaho, Indiana, Iowa, Maine, Mississippi, Nebraska, North Dakota and Tennessee." A comparison of the descriptions from two consecutive years reveals that LendingClub obtained new licenses for Kansas and North Carolina. We also check the license information obtained from the 10-K filings with the platform's lending activity in a state to confirm the accuracy of the data. Via this method, we identify the states for which the P2P platforms obtained a license after the start date of the sample period and the states for which the P2P platforms never obtained a license during the sample period.[28] For instance, neither LendingClub nor Prosper had a license to operate in the state of Iowa throughout our sample period (2009Q3-2017Q4).

We construct an IV based on the license status of LendingClub and Prosper.[29] Specifically, we use the number of quarters since both LendingClub and Prosper obtained their licenses for P2P lending business in a particular state as the IV.[30] In Table 4, we present the IV-2SLS estimation. Column (1) presents the first-stage results, while column (2) presents the second-stage results. In column (1), the IV is significantly associated with the P2P lending volume, with a t-value of 8.95. In column (2), the second-stage results show that the coefficient on the instrumented $LNP2P_{s,t-1}$ is positive and statistically significant at the 1 percent level (t-value = 3.59). Therefore, the IV-2SLS estimation lends further support to the central hypothesis that banks operating in states with a higher P2P lending volume experience more loan losses.

[Insert Table 4 Here]

V. CROSS-SECTIONAL ANALYSES

Because the empirical evidence shows that the dominant effect appears to be related to the overleveraging channel, our subsequent tests focus on verifying this channel. In this section, we conduct two cross-sectional tests to shed light on the overleveraging channel through which P2P lending can affect banks' loan losses.

The Common-Lending Effect

Our baseline results show that banks report more loan losses if they operate in a state

[28] The full list of these two types of states includes Iowa, Idaho, Indiana, Kansas, Maine, Mississippi, North Carolina, North Dakota, Nebraska, Pennsylvania, and Tennessee.

[29] In our sample period, LendingClub dominated the P2P lending market, capturing over 70 percent of the market share. Prosper was ranked No. 2 in the US market and took a much smaller market share. Results of IV-2SLS estimation are similar if we construct the IV solely based on the license status of LendingClub.

[30] Because LendingClub and Prosper's 10-K filings are only available from 2009 onward, for states where either platform has a P2P lending license at the beginning of our sample period, we assume the license was obtained in 2009Q3 (the same quarter as the beginning of our sample).

where the P2P lending volume is higher. This finding is consistent with the argument that borrowing easy money on P2P platforms leads to overleveraged individual/household borrowers, increasing banks' loan losses. In line with this channel, we argue that banks are more likely to be severely affected by P2P lending if they participate more extensively in the personal/household loan market, which is the focus of P2P lending platforms. In H2, we therefore hypothesize that the effect of P2P lending on loan losses will be stronger for banks that have greater exposure to the consumer loan market.

To test this prediction, we rely on the customer base overlap between traditional banks and P2P lending platforms to measure the former's exposure to the consumer loan market. P2P lending platforms typically serve households or individual borrowers rather than business entities. If the easy money available from such platforms leads to overleveraged individual/household borrowers, then banks with more individual/household borrowers would arguably be more severely affected. Operationally, we first use the level of consumer loans ($CSLOAN_{i,t-1}$) as the partition variable, which is calculated as the percentage of total loans, both lagged by one quarter. We also use the percentage change in consumer loans ($\Delta CSLOAN_{i,t}$) from quarter $t-1$ to t. To ease interpretation of the interaction terms, we create an indicator variable (*HIGH*) based on the quarterly median value of the corresponding partition variable. That is, *HIGH* equals 1 for banks with higher exposure to the consumer loan market, and 0 otherwise.

Table 5 presents the results of the tests of H2. In column (1), we show the results using the level of consumer loans at quarter $t-1$ as the partition variable. The coefficient on the interaction term, $LNP2P_{s,t-1} \times HIGH$, is significantly positive. This outcome is consistent with the prediction that the relation between P2P lending and loan losses is stronger for banks with greater exposure to the consumer loan market. In column (2), we show the results using the change in consumer loans from quarter $t-1$ to t as the partition variable. Again, the significantly positive coefficient on the interaction term supports our hypothesis. Taken together, using the level of and the change in consumer loans to capture banks' exposure to the consumer loan market, we provide evidence that the effect of P2P lending on loan losses is stronger when banks are more exposed to the consumer loan market. This common-lending effect corroborates the overleveraging channel through which P2P lending can affect banks' loan losses.

[Insert Table 5 Here]

The Overleveraged Consumer Effect

Our second cross-sectional hypothesis focuses on the ex ante leverage of consumers who borrow money from banks. Consumers with higher leverage are more likely to have difficulty repaying the banks, especially when the competitors (i.e., the P2P platforms) can make these consumers even more leveraged. Bank borrowers with higher leverage are more likely to reach the default threshold once the additional funding obtained from P2P platforms is included. By contrast, the additional funding from P2P lending may not be that critical if a bank's borrowers originally have lower leverage because they are probably still capable of repaying the increased level of debt. In H3, we therefore hypothesize that the effect of P2P lending on loan losses will be stronger for banks whose consumer borrowers are already more highly leveraged.

To test this prediction, we first use the extent of ex ante overleveraging at the state level to capture the likelihood that local banks' borrowers are overleveraged. The basic idea is that individuals who are more highly leveraged are more likely to be overleveraged if they also borrow from a P2P lending platform. Specifically, we use as the partition variable the weighted average of the rates of three types of household debt delinquency, lagged by one quarter. That is, the overall household delinquency rate ($DELINQ_{s,t-1}$) is calculated as (auto debt per capita × auto debt delinquency rate + credit card debt per capita × credit card debt delinquency rate + mortgage debt per capita × mortgage debt delinquency rate)/(auto debt per capita + credit card debt per capita + mortgage debt per capita). We also use the bank-level nonperforming consumer loans ($NPL\_CSL_{i,t-1}$) lagged by one quarter to capture the extent to which banks' individual/household borrowers are overleveraged. To ease interpretation of the interaction terms, we create an indicator variable (*HIGH*) based on the quarterly median value of the corresponding partition variable. That is, *HIGH* equals 1 for banks that are ex ante more likely to have overleveraged borrowers, and 0 otherwise.

Table 6 presents the results of the tests of H3. In column (1), we show the results using the state-level household delinquency rate as the partition variable. The coefficient on the interaction term, $LNP2P_{s,t-1} \times HIGH$, is significantly positive. This outcome is consistent with the prediction that the relation between P2P lending and loan losses is stronger for banks in a state with a more leveraged population ex ante. In column (2), we show the results using the lagged nonperforming consumer loans as the partition variable. Again, the significantly positive coefficient on the interaction term supports our hypothesis. Taken together, these two distinct measures, which we use to capture banks' ex ante likelihood of having overleveraged borrowers, show that the effect of P2P lending on loan losses is stronger for banks whose consumer borrowers are higher leveraged. This overleveraged consumer effect provides corroborative support for the overleveraging channel in our main hypothesis.

[Insert Table 6 Here]

VI. ADDITIONAL ANALYSES

Components of P2P Lending Volume

In this section, we explore whether different components of the P2P lending volume have different effects on banks' loan losses. This unique and interesting analysis is based on the available data from both LendingClub and Prosper. Both platforms provide data on the loan purposes as stated by the borrowers themselves when they submit their loan application. We divide the P2P lending volume into two components: (i) loans for debt consolidation ($LNP2P\_DC_{s,t-1}$), for example, for bank loan repayment and credit card payoff; and (ii) loans for other purposes ($LNP2P\_OP_{s,t-1}$), including home improvement, large purchases, medical expenses, auto, and so forth. We also divide the P2P lending volume according to lender type. For each loan in the P2P lending data, we identify whether the loan is funded by retail lenders or institutional lenders. Accordingly, we aggregate at the state-quarter level the loan volume funded by retail lenders ($LNP2P\_RT_{s,t-1}$) and the loan volume funded by institutional lenders ($LNP2P\_IS_{s,t-1}$).

To test the heterogeneous effect of different components of P2P lending volume, we put both components into the regression model. In column (1) of Table 7, we include $LNP2P\_DC_{s,t-1}$ and $LNP2P\_OP_{s,t-1}$ to test if the loan purpose matters. The coefficient on $LNP2P\_DC_{s,t-1}$ is positive and statistically significant at the 1 percent level, while the coefficient on $LNP2P\_OP_{s,t-1}$ is negative and statistically significant at the 10 percent level. The coefficient on debt consolidation loans ($LNP2P\_DC_{s,t-1}$) is significantly larger than that on the loans taken out for other purposes, and thus our main finding is likely driven by loans borrowed for debt consolidation purpose.[31] This outcome is consistent with our intuition that individuals on the verge of default are more likely to borrow money from P2P platforms to repay their bank debt.

In column (2) of Table 7, we include $LNP2P\_RT_{s,t-1}$ and $LNP2P\_IS_{s,t-1}$ to test if the lender type matters. We find that the coefficients on both $LNP2P\_RT_{s,t-1}$ and $LNP2P\_IS_{s,t-1}$ are significantly positive. The coefficient on loans funded by institutional lenders ($LNP2P\_RT_{s,t-1}$) is significantly smaller than that on loans extended by retail lenders, suggesting that institutional lenders have higher screening ability and maintain a higher

[31] In an untabulated analysis, we examine whether the FICO scores of borrowers who stated the loan purpose as debt consolidation are different from those who stated other loan purposes. Using a sample of P2P loans from 2009Q3 to 2017Q4, we find that the FICO score of the former (latter) type of borrowers to be 694 (702) and the difference is statistically significant at the 1% level.

lending standard. Thus the institutional loan volume has smaller spillover effects on banks' loan losses.

[Insert Table 7 Here]

Exploring the Role of Accounting Discretion

Prior literature suggests that banks managers have wide latitude for discretion in the estimation process of loan loss provisions (e.g., Beatty, Chamberlain, and Magliolo, 1995; Kanagaretnam, Lobo, and Yang, 2004; Liu and Ryan, 2006; Kilic, Lobo, Ranasinghe, and Sivaramakrishnan, 2013). In this section, we explore whether the effect of P2P lending on banks' reported loan losses varies according to their capacity to make loan loss provisions. Because higher-capacity banks have more flexibility in making loan loss provisions, they are expected to make sufficient provisions when their borrowers become overleveraged due to P2P borrowing. Loan loss provisions will lower banks' net earnings, adversely affecting bank managers' performance evaluation. As a result, lower-capacity banks may not be able to make sufficient loan loss provisions in response to their borrowers' overleveraging issue due to P2P borrowing. Therefore, we conjecture that the effect of P2P lending on banks' reported loan losses will be stronger for banks with a higher capacity to make loan loss provisions.

To test this conjecture, we divide our sample banks into higher-capacity and lower-capacity banks based on their earnings before loan loss provisions. Banks with higher earnings before loan loss provisions enjoy greater freedom or possess more capacity in the sense that they are less likely to be constrained by the downward earnings pressure of loan loss provisioning. Similarly, we also divide banks into two groups based on their regulatory capital ratio. Capital adequacy is the most prominent aspect of banking regulation. Regulators check at random times to make sure that banks are complying with the capital requirement (Repullo and Suarez 2013). To reduce the risk of losing their valuable charter in case of failure, banks typically operate well above the minimum capital adequacy ratio (Elizalde and

Repullo 2007). Under the current regulatory regime, loan loss provisioning creates downward pressure on the capital ratio. Therefore, banks with a higher capital ratio have more flexibility or capacity to make loan loss provisions. Accordingly, we create an indicator variable (*HIGH*) that equals 1 for banks with a higher capacity to make loan loss provisions (i.e., with a capacity that is higher than the state-quarter median), and 0 otherwise. We then include the interaction term between this dummy variable and the P2P lending volume in the regression model.

Table 8 presents the results. In column (1), we show the results when capacity is measured using the current quarter earnings before loan loss provisions. The coefficient on the interaction term, $LNP2P_{s,t-1} \times HIGH$, is significantly positive. This outcome is consistent with the prediction that the effect of P2P lending on banks' reported loan losses is stronger for banks with a higher capacity to make loan loss provisions. In column (2), we use the risk-based tier 1 capital ratio at the beginning of the current quarter to capture banks' capacity to make loan loss provisions. Again, we continue to find a significantly positive coefficient on the interaction term. Overall, measuring banks' capacity to make loan loss provisions from two different perspectives yields consistent evidence suggesting that the relation between P2P lending and banks' reported loan losses is stronger for higher-capacity banks. This finding highlights the moderating role of accounting discretion.

[Insert Table 8 Here]

The Effect of P2P Lending on Banks' Future Charge-Offs

The analyses in the previous sections have focused on the effect of P2P lending on banks' loan losses provisions. The central argument is that individuals borrowing on P2P platforms are likely to be overleveraged. Bank managers respond to this overleveraging by reporting more loan loss provisions. While loan loss provisions capture bank managers' estimation of loan losses and gives a timelier indication of the loan losses faced by the banks during the circumstances occurring within a fiscal period, loan charge-offs reflect realized losses (i.e., confirmed borrower defaults). Taking advantage of the natural accounting link between loan loss provisions and future charge-offs, we formally test whether P2P lending is associated with future realized loan losses. This test can validate our central argument and provide confirmation of the overleveraging channel: to the extent that individuals borrowing on P2P platforms are likely to be overleveraged, the P2P lending volume is also expected to increase future loan charge-offs because overleveraged individuals are more likely to default in the future.

To examine the relation between P2P lending and bank borrowers' future defaults, we run the following OLS model:

$$\begin{aligned} CO\_CSL_{i,t+1} = {} & \beta_0 + \beta_1 LNP2P_{s,t-1} + \beta_2 SIZE_{i,t-1} + \beta_3 EBP_{i,t} + \beta_4 CAPR1_{i,t-1} \\ & + \beta_5 ALW_{i,t-1} + \beta_6 HHI_{i,t-1} + \beta_7 HETE_{i,t-1} + \beta_8 \Delta LOAN_{i,t} + \beta_9 \Delta GDP_{i,t} \\ & + \beta_{10} \Delta UNEMP_{i,t} + \beta_{11} \Delta HPI_{i,t} + \beta_{12} \Delta POP_{i,t} + \beta_{13} GDP_{i,t-1} \\ & + \beta_{14} UNEMP_{i,t-1} + \beta_{15} HPI_{i,t-1} + \beta_{16} POP_{i,t-1} + \beta_{17} AUTOD_{i,t-1} \\ & + \beta_{18} CCD_{i,t-1} + \beta_{19} MORTD_{i,t-1} + \beta_{20} DELINQ_{i,t-1} + bank\ fixed\ effects \\ & + quarter\ fixed\ effects + \varepsilon_{i,t}. \qquad (2) \end{aligned}$$

In Equation (2), the dependent variable ($CO\_CSL_{i,t+1}$) is bank *i*'s net charge-offs of consumer loans in quarter *t*+1, scaled by its total outstanding consumer loans at quarter *t*. In addition, we are also interested in the overall effect of P2P lending on banks' total charge-offs. Therefore, we use the total charge-offs ($CO_{i,t+1}$) as an alternative dependent variable. We focus on the coefficient on the P2P lending variable ($LNP2P_{s,t-1}$), that is, β_1. A significantly positive β_1 would validate the proposed overleveraging channel.

Table 9 presents the results. Column (1) uses future-one-quarter charge-offs of consumer loans as the dependent variable while column (2) uses the future-one-quarter total charge-offs. The results are qualitatively the same in both columns: the coefficients on $LNP2P_{s,t-1}$ are significantly positive. These results justify bank managers' expectations about the impact of P2P lending on loan losses. Put differently, this additional test on future charge-offs provides direct evidence that our main results are driven by the borrowers' deteriorating condition rather than bank managers' behavioral bias. This deteriorating condition is in keeping with the overleveraging channel proposed in our main hypothesis.

[Insert Table 9 Here]

VII. CONCLUSIONS

In this paper, we investigate the relation between P2P lending and traditional banks' loan losses. Using a sample of single-state banks' quarterly observations from 2009 to 2017, we document that banks' loan loss provisions increase as P2P lending booms. This main finding is statistically and economically significant. Results from the IV approach suggest a causal effect of P2P lending on banks' loan losses. We also find that the positive relation between P2P lending and loan losses is stronger for banks that have greater exposure to the consumer loan market and for banks whose consumer borrowers are more highly leveraged. These results are consistent with the view that the easy money available on P2P lending platforms leads to overleveraged individual/household borrowers and increases their repayment risk.

In additional analyses, we provide further insights by showing that P2P loans for the purpose of debt consolidation drive our main finding. We also highlight the moderating role of accounting discretion by showing that the relation between P2P lending and reported loan losses is stronger for banks with a higher capacity to make loan loss provisions. Finally, we further justify the overleveraging channel by showing directly that P2P lending is positively associated with banks' future charge-offs (i.e., confirmed borrowers' defaults).

Our study adds to the banking literature by documenting a new determinant of loan loss provisions. More importantly, our results also contribute to the growing literature that examines the impact of FinTech development. FinTech companies play an increasingly important role in the financial system and have attracted both regulatory and media attention. Leveraging the available data on P2P lending, we are among the first to study the interaction between FinTech firms and traditional financial institutions.

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Appendix A: Variable Definitions and Data Sources

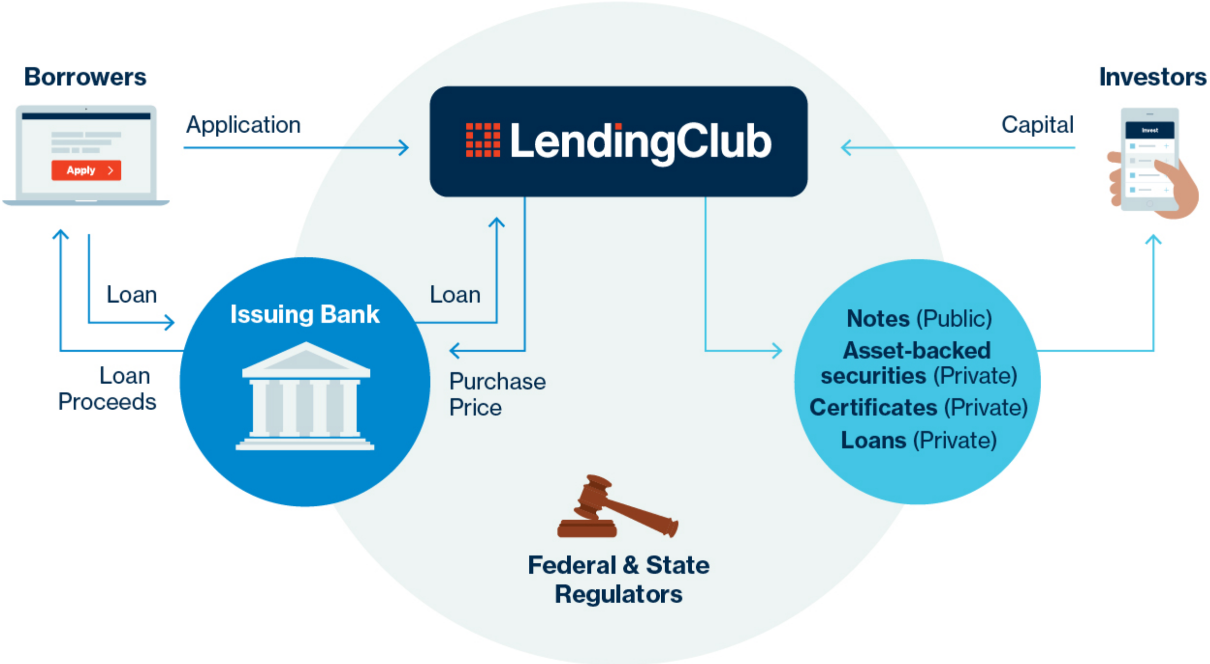
This table summarizes the definitions and data sources of the variables used in the regression analyses.

Variable	Definition	Data Source
State-level P2P lending variables:		
$LNP2P_{s,t-1}$	Natural logarithm of 1 plus the state-quarter aggregate loan volumes (in billion US dollars) originated by LendingClub and Prosper during quarter $t-1$.	LendingClub and Prosper
$P2PPOP_{s,t-1}$	The state-quarter aggregate loan volumes originated by LendingClub and Prosper during quarter $t-1$ scaled by the state population.	LendingClub and Prosper
$P2PBAL_{s,t-1}$	The state-quarter aggregate outstanding loan balance originated by LendingClub at the end of quarter $t-1$ scaled by the state population.	LendingClub
$P2PNPL_{s,t-1}$	The state-quarter aggregate nonperforming P2P loans scaled by the outstanding loan balance originated by LendingClub at the end of quarter $t-1$.	LendingClub
$LNP2P\_DC_{s,t-1}$	Natural logarithm of 1 plus the state-quarter aggregate loan volumes (in billion US dollars) for debt consolidation purpose during quarter $t-1$.	LendingClub and Prosper
$LNP2P\_OP_{s,t-1}$	Natural logarithm of 1 plus the state-quarter aggregate loan volumes (in billion US dollars) for other purposes during quarter $t-1$.	LendingClub and Prosper
$LNP2P\_RT_{s,t-1}$	Natural logarithm of 1 plus the state-quarter aggregate loan volumes (in billion US dollars) funded by retail lenders during quarter $t-1$.	LendingClub and Prosper
$LNP2P\_IS_{s,t-1}$	Natural logarithm of 1 plus the state-quarter aggregate loan volumes (in billion US dollars) funded by institutional lenders during quarter $t-1$.	LendingClub and Prosper
Bank-level variables:		
$LLP_{i,t}$	Loan loss provisions in quarter t scaled by the lagged total loans of bank i.	Call reports
$SIZE_{i,t-1}$	The natural log of total assets at the end of quarter $t-1$.	Call reports
$EBP_{i,t}$	Earnings before taxes and loan loss provisions in quarter t scaled by the lagged total loans.	Call reports
$CAPR1_{i,t-1}$	Tier 1 risk-adjusted capital ratio at the end of quarter $t-1$.	Call reports
$ALW_{i,t-1}$	Loan loss allowance in quarter $t-1$ scaled by total loans in quarter $t-1$.	Call reports
$HHI_{i,t-1}$	Banking industry competition measured by the Herfindahl-Hirschman Index, calculated based on the distribution of deposits within each state at quarter $t-1$.	Call reports; SOD
$HETE_{i,t-1}$	Heterogeneous loans of bank i in quarter $t-1$, calculated as the sum of commercial loans, industrial loans and commercial real estate loans divided by the total outstanding loans.	Call reports
$\Delta LOAN_{i,t}$	Change in total loans from quarter $t-1$ to quarter t scaled by total	Call reports

	loans in quarter $t-1$.	
$NPL_{i,t-1}$	Nonperforming loans in quarter $t-1$ scaled by total loans in quarter $t-1$.	Call reports
$CO_{i,t}$	Net charge-offs in quarter t scaled by total loans in quarter $t-1$.	Call reports
$\Delta NPL_{i,t}$	Change in nonperforming loans from quarter $t-1$ to quarter t scaled by total loans in quarter $t-1$.	Call reports
$\Delta NPL_{i,t-1}$	Change in nonperforming loans from quarter $t-2$ to quarter $t-1$ scaled by total loans in quarter $t-1$.	Call reports
$\Delta NPL_{i,t-2}$	Change in nonperforming loans from quarter $t-3$ to quarter $t-2$ scaled by total loans in quarter $t-1$.	Call reports
$D\Delta NPL_{i,t}$	Dummy variable that equals 1 if $\Delta NPL_{i,t}$ is negative, and 0 otherwise.	Call reports
$CSLOAN_{i,t-1}$	Level of consumer loans at the end of quarter $t-1$ scaled by total loans in quarter $t-1$.	Call reports
$\Delta CSLOAN_{i,t}$	Change in consumer loans from quarter $t-1$ to t scaled by the consumer loan balance in quarter $t-1$.	Call reports
$NPL\_CSL_{i,t-1}$	Nonperforming consumer loans at the end of quarter $t-1$ scaled by the consumer loan balance in quarter $t-1$.	Call reports
$CO\_CSL_{i,t+1}$	Net charge-offs of consumer loans in quarter $t+1$ scaled by the consumer loan balance in quarter t.	Call reports
$CO\_TTL_{i,t+1}$	Net charge-offs of total loans in quarter $t+1$ scaled by total outstanding loans in quarter t.	Call reports
State level control variables:		
$\Delta GDP_{s,t}$	The growth rate (in %) of state GDP per capita from quarter $t-1$ to quarter t.	BEA
$\Delta UNEMP_{s,t}$	Change in state unemployment rate from quarter $t-1$ to quarter t.	US BLS
$\Delta HPI_{s,t}$	The appreciation rate of the state-level house price index from quarter $t-1$ to quarter t.	US FHFA
$\Delta POP_{s,t}$	Percentage change in the state population from quarter $t-1$ to quarter t.	BEA
$GDP_{s,t-1}$	Log of the state-level GDP per capita (in $) in quarter $t-1$.	BEA
$UNEMP_{s,t-1}$	The state-level unemployment rate (in %) in quarter $t-1$.	US BLS
$HPI_{s,t-1}$	Log of the state-level house price index in quarter $t-1$.	US FHFA
$POP_{s,t-1}$	Log of state population in quarter $t-1$.	BEA
$AUTOD_{s,t-1}$	Log of the state-level auto debt balance per capita (in $) in quarter $t-1$.	FRBNY
$CCD_{s,t-1}$	Log of the state-level credit card debt balance per capita (in $) in quarter $t-1$.	FRBNY
$MORTD_{s,t-1}$	Log of the state level mortgage debt balance per capita (in $) in quarter $t-1$.	FRBNY

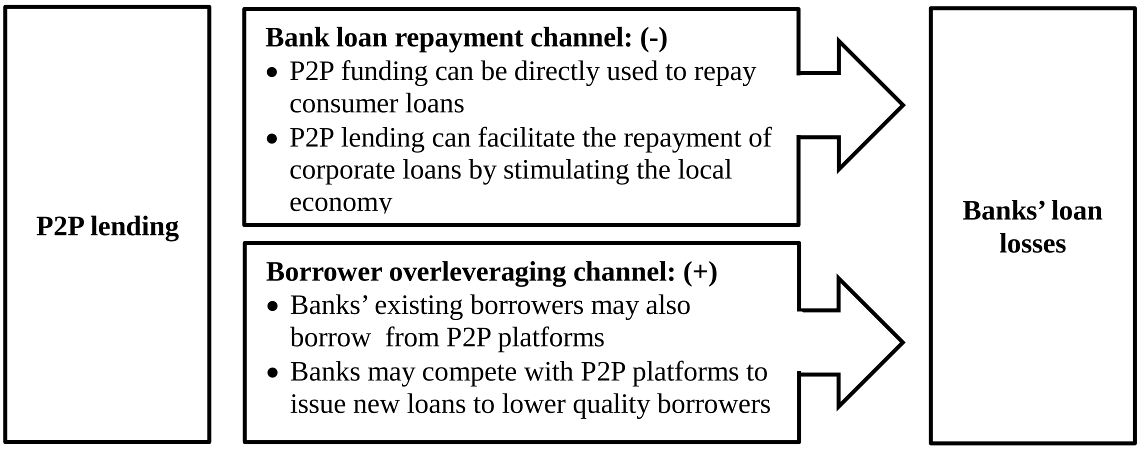
$DELINQ_{s,t-1}$	Household debt delinquency rate in quarter $t-1$, calculated as the sum of per capita auto debt, credit card debt and mortgage debt balance that is 90 days or more delinquent, divided by the sum of per capita auto debt, credit card debt and mortgage debt balance.	FRBNY
Instrumental variable:		
$LICENSEQTR_{s,t-1}$	The number of quarters since both LendingClub and Prosper obtained their license for P2P lending business in a particular state.	LendingClub, Prosper, and their 10-K filings

Figure 1 Loan issuance mechanism



This flow chart illustrates the loan issuance mechanism of P2P lending platforms during our sample period starting in 2009. This figure is extracted from LendingClub's 10-K for fiscal year 2018, filed with the SEC. Prosper's loan issuance mechanism is essentially the same (i.e., it uses the same business model as LendingClub). Borrowers submit loan applications through the online platform. The platform then evaluates the borrowers' information and provides them with various loan options including the loan term, amount, and interest rate. The loan option selected by the applicant will be listed on the platform to attract investor commitments. Once sufficient commitments are received, the issuing bank originates the loan to the applicant. Shortly after the loan is issued, the platform uses the proceeds from investors to purchase the loan from the issuing bank. Finally, the platform issues new securities (e.g., the borrower payment-dependent notes) to investors who are committed to funding the loan.

Figure 2 Summary of arguments and counter-arguments in Hypothesis 1



This figure summarizes the arguments and counter-arguments in Hypothesis 1. Banks' existing borrowers may also borrow from P2P platforms, and banks may also compete with P2P platforms to issue new loans to lower-quality borrowers. Either way, banks' individual/household borrowers will become more leveraged. This borrower overleveraging channel predicts a positive relation between P2P lending and banks' loan losses. While the bank loan repayment channel predicts the opposite and creates tension with this hypothesis, prior literature shows that borrowers can eventually be overleveraged even though they use the borrowed P2P funding to repay their bank debt. Therefore, on balance, we predict that banks will suffer more loan losses when the local P2P lending market is more developed.

Figure 3 Time trend of P2P lending development

Figure 3A: Quarterly loan volume originated by LendingClub

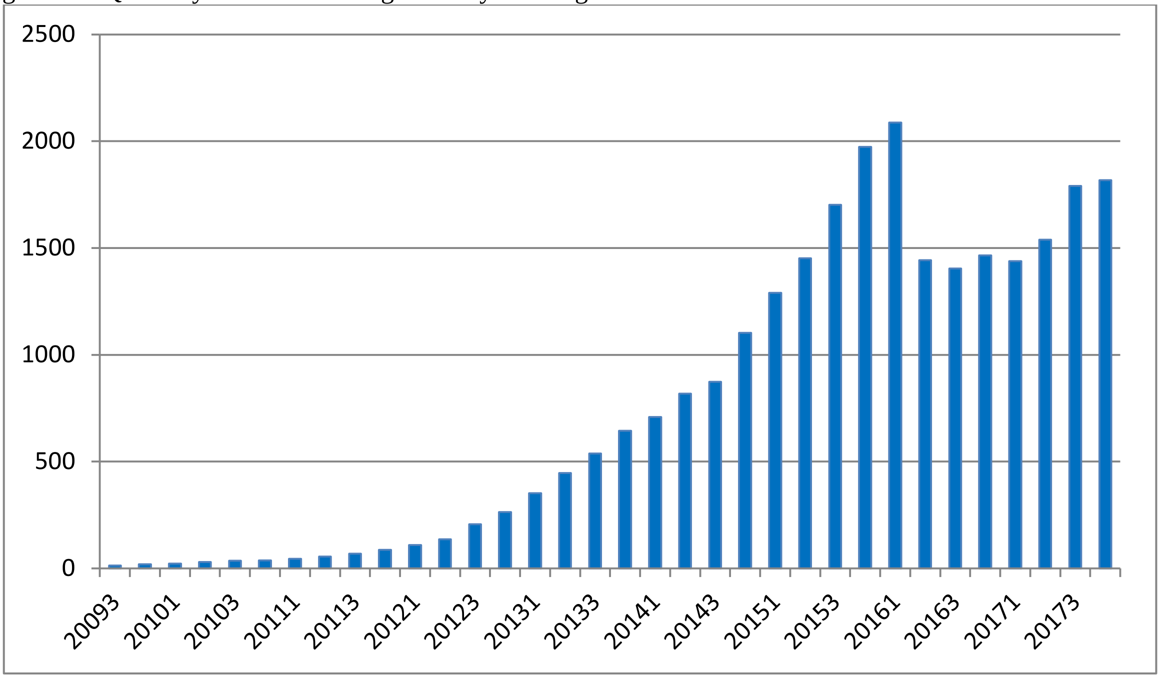
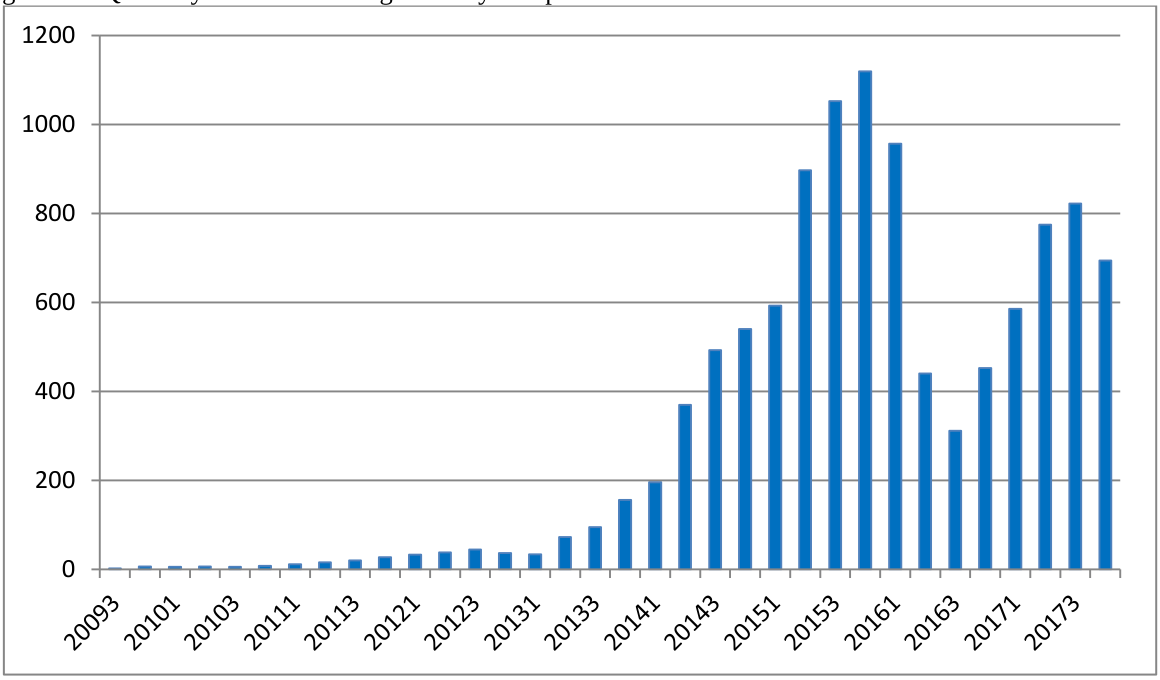


Figure 3B: Quarterly loan volume originated by Prosper



These two histograms depict the loan volume (in millions of US dollars) originated in each quarter within the sample period (2009Q3-2017Q4) for LendingClub (Figure 3A) and Prosper (Figure 3B).

Figure 4 Geographic distribution of P2P lending volume

Figure 4A: LendingClub's loan issuance by state

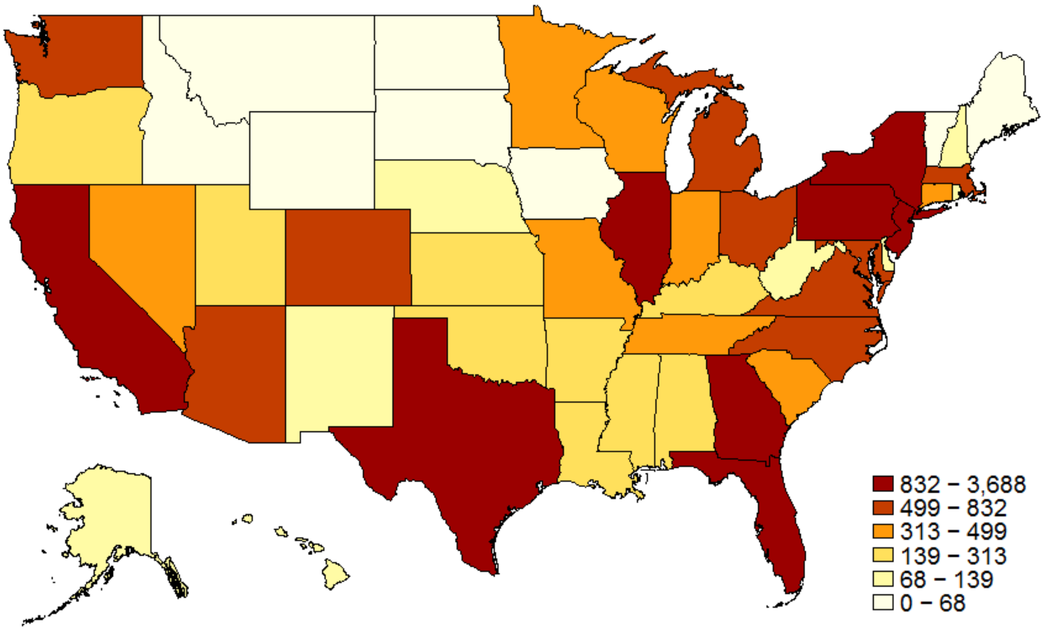
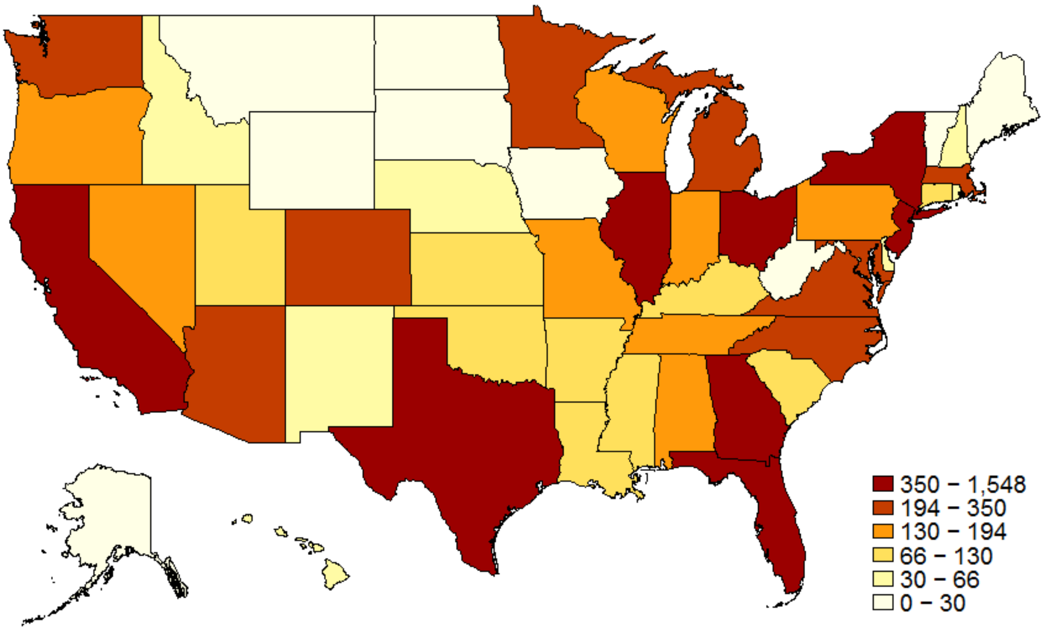


Figure 4B: Prosper's loan issuance by state



This figure depicts the geographic distribution of the loan volume (in millions of US dollars) originated during the entire sample period (2009Q3-2017Q4) for LendingClub (Figure 4A) and Prosper (Figure 4B).

Figure 5 Funding purposes of P2P loans

Figure 5A: Borrowers' funding usage distribution for LendingClub

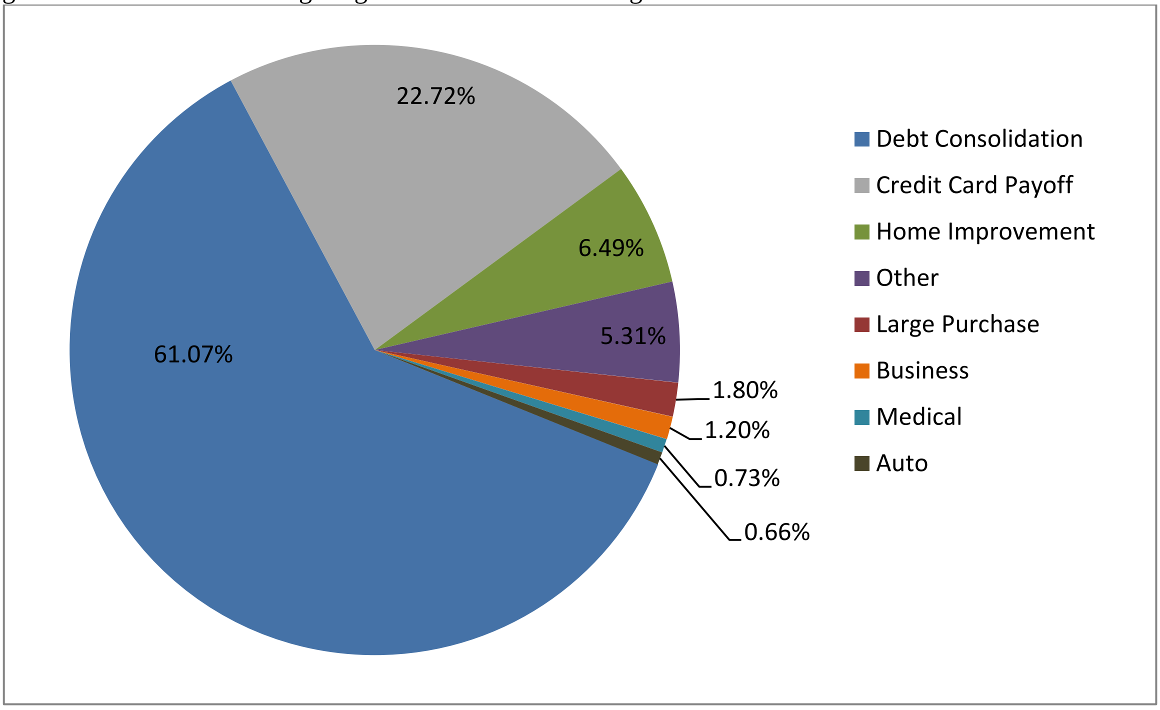
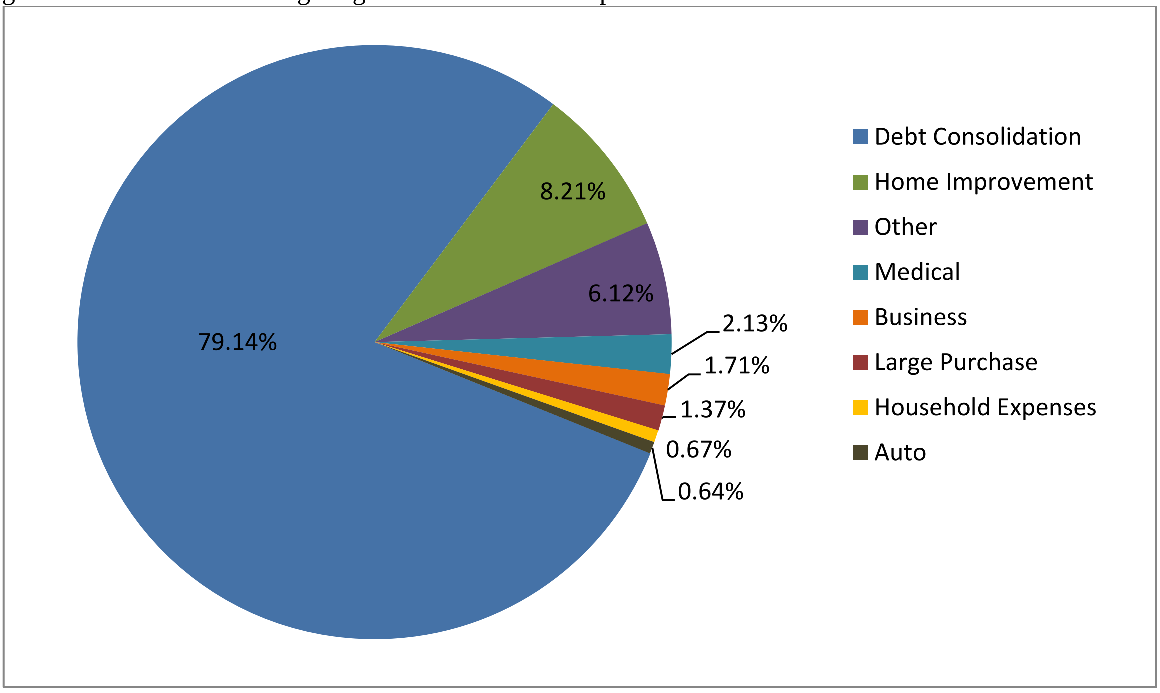


Figure 5B: Borrowers' funding usage distribution for Prosper



These two pie charts depict the funding purpose distribution of loans originated during the entire sample period (2009Q3-2017Q4) for LendingClub (Figure 5A) and Prosper (Figure 5B).

Figure 6 Investor composition of P2P lending volume

Figure 6A: Individual vs. institutional investors' lending volume for LendingClub

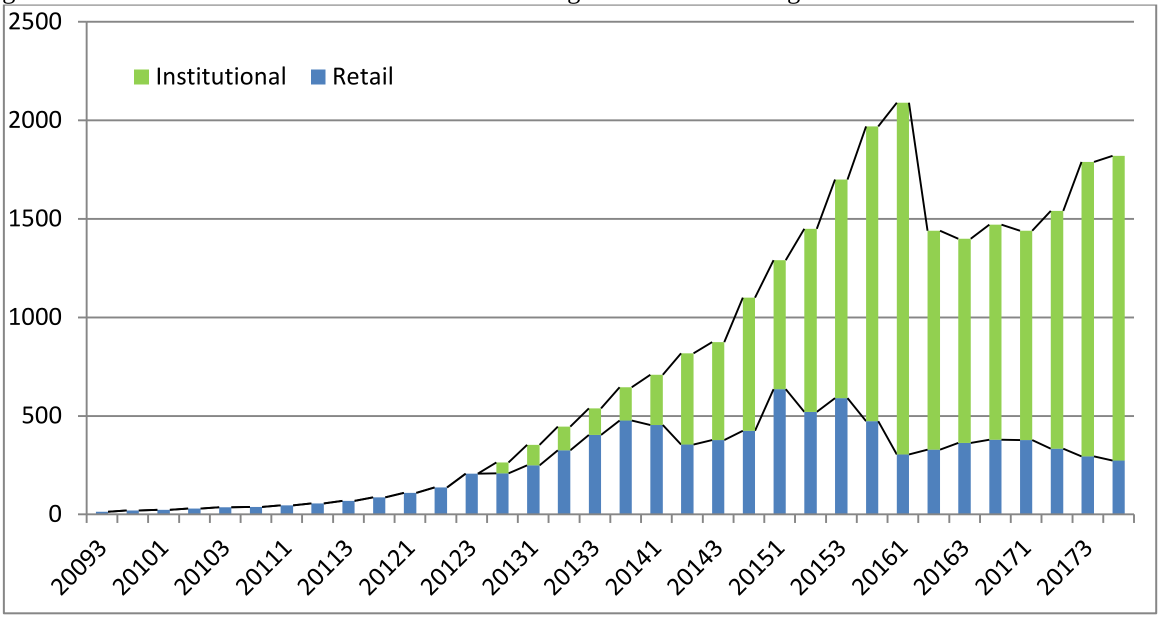
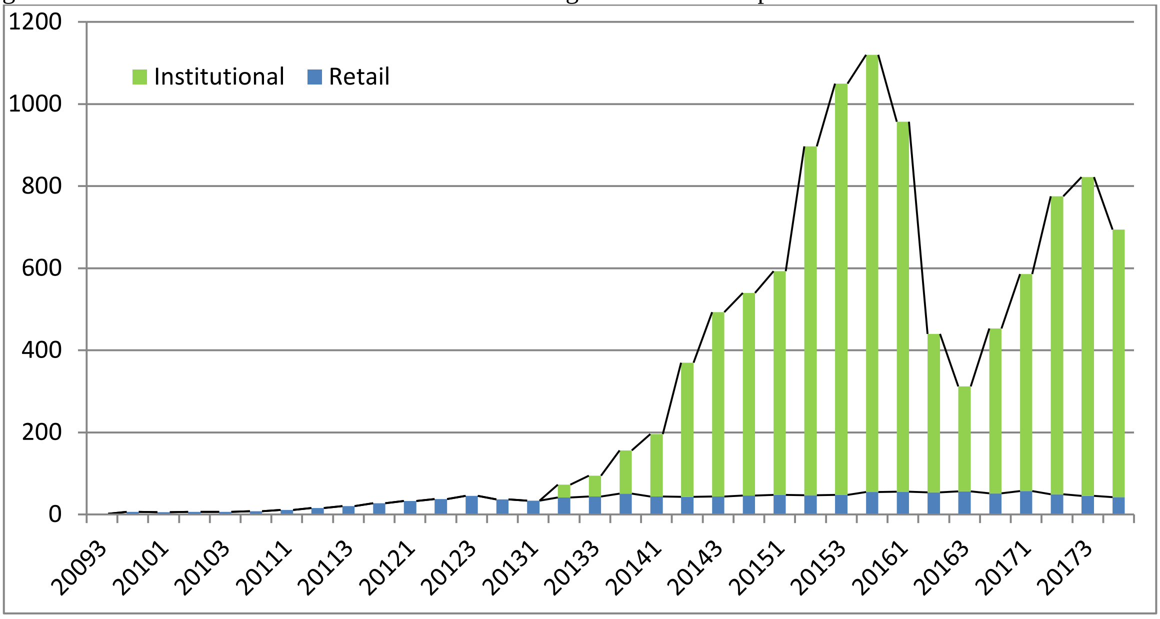


Figure 6B: Individual vs. institutional investors' lending volume for Prosper



These two figures depict the investor composition of loans originated during the entire sample period (2009Q3-2017Q4). After the introduction of institutional investors, loan applications are randomly assigned to either the fractional pool or the whole purchase pool. While individual investors can only provide funding to the fractional pool, institutional investors can only lend money to the whole pool. Figures 6A and 6B show the evolution for LendingClub and Prosper, respectively.

Table 1 Summary statistics

	Mean	SD	25%	Median	75%
$LLP_{i,t}$	0.0012	0.0028	0.0000	0.0004	0.0012
$LNP2P_{s,t-1}$	0.0258	0.0448	0.0008	0.0060	0.0297
$SIZE_{i,t-1}$	12.0087	1.1051	11.2590	11.9315	12.6669
$EBP_{i,t}$	0.0051	0.0049	0.0029	0.0049	0.0070
$CAPR1_{i,t-1}$	0.1732	0.0817	0.1235	0.1502	0.1945
$ALW_{i,t-1}$	0.0170	0.0096	0.0112	0.0146	0.0199
$HHI_{i,t-1}$	0.0815	0.0606	0.0439	0.0722	0.0912
$HETE_{i,t-1}$	0.2187	0.1850	0.0828	0.1569	0.3127
$\Delta LOAN_{i,t}$	0.0100	0.0490	−0.0162	0.0065	0.0313
$\Delta GDP_{s,t}$	0.5993	1.4039	0.0425	0.8016	1.4356
$\Delta UNEMP_{s,t}$	−0.1328	0.2175	−0.2667	−0.1333	0.0000
$\Delta HPI_{s,t}$	0.0041	0.0133	−0.0029	0.0057	0.0124
$\Delta POP_{s,t}$	0.3226	0.4390	0.0342	0.1933	0.3925
$GDP_{s,t-1}$	11.0681	0.1707	10.9520	11.0786	11.2032
$UNEMP_{s,t-1}$	6.7035	2.1926	4.9000	6.5000	8.2000
$HPI_{s,t-1}$	5.7053	0.2444	5.5224	5.6717	5.7995
$POP_{s,t-1}$	15.4549	0.8872	14.8675	15.3751	16.0994
$AUTOD_{s,t-1}$	8.1171	0.2110	7.9586	8.0895	8.2506
$CCD_{s,t-1}$	7.9227	0.1656	7.7956	7.9230	8.0359
$MORTD_{s,t-1}$	10.2269	0.2975	10.0485	10.1286	10.4332
$DELINQ_{s,t-1}$	4.2530	2.6887	2.5366	3.6916	4.9495
Obs.			201,056		

This table presents the mean, standard deviation (SD), 25th percentile (25%), median, and the 75th percentile (75%) of the variables for the sample period from 2009Q3 to 2017Q4. All continuous variables are winsorized at the 1st and 99th percentiles. Variable definitions are summarized in Appendix A.

Table 2 Relation between P2P lending and banks' loan losses (H1)

Dep. Var =	(1) $LLP_{i,t}$	(2) $LLP_{i,t}$
$\boldsymbol{LNP2P_{s,t-1}}$	**0.0045***** **(5.84)**	**0.0040***** **(5.40)**
$SIZE_{i,t-1}$		0.0013*** (6.83)
$EBP_{i,t}$		−0.0201** (−2.27)
$CAPR1_{i,t-1}$		0.0013 (1.58)
$ALW_{i,t-1}$		−0.0056 (−0.79)
$HHI_{i,t-1}$		−0.0031*** (−3.61)
$HETE_{i,t-1}$		0.0028*** (7.93)
$\Delta LOAN_{i,t}$		−0.0025*** (−4.02)
$\Delta GDP_{s,t}$	−0.0000 (−0.44)	−0.0000 (−0.26)
$\Delta UNEMP_{s,t}$	0.0003*** (3.03)	0.0003*** (2.79)
$\Delta HPI_{s,t}$	−0.0119*** (−3.44)	−0.0072** (−2.47)
$\Delta POP_{s,t}$	−0.0005*** (−3.07)	−0.0005*** (−3.12)
$GDP_{s,t-1}$	0.0009 (1.33)	−0.0002 (−0.26)
$UNEMP_{s,t-1}$	0.0001*** (4.19)	0.0001** (2.72)
$HPI_{s,t-1}$	−0.0019*** (−2.85)	−0.0021*** (−3.04)
$POP_{s,t-1}$	−0.0015** (−2.14)	−0.0012* (−1.90)
$AUTOD_{s,t-1}$	0.0027*** (2.88)	0.0025*** (2.84)
$CCD_{s,t-1}$	0.0017** (2.18)	0.0014** (2.04)
$MORTD_{s,t-1}$	0.0047*** (4.91)	0.0041*** (4.29)
$DELINQ_{s,t-1}$	0.0001* (1.83)	0.0000 (1.45)
Bank fixed effects	Yes	Yes
Year-quarter fixed effects	Yes	Yes
N	201,056	201,056
adj. R^2	0.330	0.344

This table presents the baseline results of testing H1. The dependent variable is loan loss provisions ($LLP_{i,t}$), defined as the loan loss provisions of bank i in quarter t scaled by the lagged total outstanding loans. The independent variable is P2P lending ($LNP2P_{s,t-1}$), defined as the natural logarithm of 1 plus the state-quarter aggregate loan volumes (in $B) originated by LendingClub and Prosper during quarter $t-1$. All other variables are defined in Appendix A. All continuous variables are winsorized at the 1st and 99th percentiles. Constant terms are estimated but untabulated. The model includes bank fixed effects and year-quarter fixed effects; t-values, based on robust standard errors two-way clustered by bank and year-quarter, are reported in parentheses. ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively.

Table 3 Robustness checks

Dep. Var. = $LLP_{i,t}$	(1) Alternative model	(2) Alternative model	(3) Alternative P2P measure	(4) Alternative P2P measure	(5) Alternative P2P measure	(6) Excluding Iowa	(7) Excluding California	(8) Larger sample including multistate banks	(9) Smaller sample excluding M&A observations
$\boldsymbol{LNP2P_{s,t-1}}$	**0.0020*** (5.02)**	**0.0023*** (5.24)**				**0.0041*** (5.48)**	**0.0047*** (5.50)**	**0.0039*** (5.72)**	**0.0041*** (5.48)**
$\boldsymbol{P2PPOP_{s,t-1}}$			**0.0037** (2.54)**						
$\boldsymbol{P2PBAL_{s,t-1}}$				**0.0119** (2.71)**					
$\boldsymbol{P2PNPL_{s,t-1}}$					**0.0011** (2.14)**				
$NPL_{i,t-1}$	0.0194*** (13.83)								
$CO_{i,t}$	0.6163*** (22.69)	0.6210*** (22.81)							
$\Delta NPL_{i,t}$	0.0390*** (15.08)	0.0440*** (12.60)							
$\Delta NPL_{i,t-1}$		0.0086*** (7.01)							
$\Delta NPL_{i,t-2}$		0.0087*** (5.73)							
$D\Delta NPL_{i,t}$		−0.0000 (−0.17)							
$D\Delta NPL_{i,t} \times \Delta NPL_{i,t}$		−0.0284*** (−8.79)							
$SIZE_{i,t-1}$	0.0003*** (4.01)	0.0004*** (5.54)	0.0013*** (6.93)	0.0013*** (6.93)	0.0013*** (6.91)	0.0013*** (6.68)	0.0013*** (6.80)	0.0012*** (6.78)	0.0015*** (7.35)
$EBP_{i,t}$	0.0073 (1.42)	−0.0002 (−0.04)	−0.0209** (−2.34)	−0.0209** (−2.34)	−0.0209** (−2.33)	−0.0208** (−2.26)	−0.0215** (−2.42)	−0.0132 (−1.47)	−0.0259** (−2.73)
$CAPR1_{i,t-1}$	0.0024*** (3.41)	0.0020*** (3.13)	0.0013 (1.55)	0.0013 (1.55)	0.0013 (1.53)	0.0015 (1.67)	0.0015* (1.75)	0.0011 (1.41)	0.0011 (1.48)
$ALW_{i,t-1}$	−0.1017*** (−10.06)	−0.0835*** (−8.90)	−0.0046 (−0.64)	−0.0046 (−0.64)	−0.0046 (−0.64)	−0.0050 (−0.69)	−0.0051 (−0.70)	0.0018 (0.25)	−0.0052 (−0.83)

$HHI_{i,t-1}$	−0.0019***	−0.0019***	−0.0035***	−0.0035***	−0.0031***	−0.0033***	−0.0018**	−0.0030***	−0.0027***
	(−3.82)	(−3.85)	(−3.76)	(−3.73)	(−3.61)	(−3.57)	(−2.35)	(−3.64)	(−3.52)
$HETE_{i,t-1}$	0.0015***	0.0016***	0.0028***	0.0028***	0.0028***	0.0028***	0.0028***	0.0028***	0.0028***
	(8.33)	(9.63)	(7.94)	(7.93)	(7.87)	(7.95)	(8.11)	(7.87)	(8.67)
$\Delta LOAN_{i,t}$	0.0001	−0.0003	−0.0025***	−0.0025***	−0.0025***	−0.0025***	−0.0025***	−0.0024***	−0.0036***
	(0.28)	(−0.97)	(−4.01)	(−4.02)	(−4.03)	(−3.97)	(−4.23)	(−4.02)	(−4.60)
$\Delta GDP_{s,t}$	0.0000	−0.0000	−0.0000	−0.0000	−0.0000	−0.0000	0.0000	−0.0000	0.0000
	(0.15)	(−0.33)	(−0.55)	(−0.61)	(−0.63)	(−0.01)	(0.73)	(−0.49)	(0.01)
$\Delta UNEMP_{s,t}$	0.0002***	0.0002***	0.0002**	0.0002**	0.0002**	0.0003***	0.0002*	0.0003***	0.0002**
	(3.01)	(2.85)	(2.47)	(2.40)	(2.38)	(2.96)	(1.98)	(2.96)	(2.45)
$\Delta HPI_{s,t}$	−0.0026	−0.0026	−0.0072**	−0.0071**	−0.0070**	−0.0079**	−0.0096***	−0.0079**	−0.0073***
	(−1.52)	(−1.56)	(−2.48)	(−2.46)	(−2.35)	(−2.71)	(−2.88)	(−2.66)	(−2.96)
$\Delta POP_{s,t}$	−0.0003***	−0.0003***	−0.0004***	−0.0004***	−0.0004***	−0.0005***	−0.0004***	−0.0005***	−0.0004***
	(−3.44)	(−3.26)	(−3.20)	(−3.17)	(−3.21)	(−3.17)	(−2.74)	(−3.16)	(−3.27)
$GDP_{s,t-1}$	0.0004	0.0001	−0.0001	−0.0001	−0.0003	−0.0002	0.0005	−0.0004	0.0000
	(1.11)	(0.19)	(−0.24)	(−0.23)	(−0.54)	(−0.32)	(0.91)	(−0.68)	(0.02)
$UNEMP_{s,t-1}$	0.0000	0.0001**	0.0001**	0.0001**	0.0001*	0.0001**	0.0001***	0.0001***	0.0001***
	(1.67)	(2.38)	(2.21)	(2.32)	(1.85)	(2.61)	(3.03)	(3.16)	(2.96)
$HPI_{s,t-1}$	−0.0011**	−0.0014***	−0.0011*	−0.0011*	−0.0009	−0.0020***	−0.0020***	−0.0018***	−0.0020***
	(−2.69)	(−3.32)	(−1.80)	(−1.77)	(−1.59)	(−3.03)	(−3.10)	(−2.99)	(−3.41)
$POP_{s,t-1}$	−0.0008*	−0.0006	−0.0011*	−0.0011*	−0.0010	−0.0012*	−0.0015*	−0.0008*	−0.0015**
	(−1.86)	(−1.51)	(−1.71)	(−1.70)	(−1.61)	(−1.86)	(−1.94)	(−1.96)	(−2.41)
$AUTOD_{s,t-1}$	0.0014***	0.0012**	0.0022**	0.0022**	0.0020**	0.0027***	0.0009*	0.0025***	0.0021**
	(3.03)	(2.65)	(2.39)	(2.41)	(2.30)	(2.76)	(1.81)	(2.81)	(2.68)
$CCD_{s,t-1}$	0.0012**	0.0009*	0.0018**	0.0017**	0.0021***	0.0012*	0.0011*	0.0011*	0.0014**
	(2.67)	(2.03)	(2.56)	(2.43)	(3.22)	(1.82)	(1.78)	(1.73)	(2.12)
$MORTD_{s,t-1}$	0.0022***	0.0024***	0.0040***	0.0039***	0.0038***	0.0042***	0.0052***	0.0037***	0.0036***
	(4.13)	(4.78)	(4.17)	(4.15)	(4.28)	(4.34)	(4.97)	(4.20)	(4.24)
$DELINQ_{s,t-1}$	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0001**
	(0.21)	(1.12)	(1.09)	(1.13)	(0.89)	(1.34)	(0.61)	(1.50)	(2.44)
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-quarter fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	200,432	199,835	201,056	201,056	201,056	190,667	194,442	221,854	165,121
adj. R^2	0.603	0.597	0.343	0.343	0.343	0.347	0.341	0.353	0.343

This table presents a robustness check for the baseline results. The dependent variable is loan loss provisions ($LLP_{i,t}$), defined as the loan loss provisions of bank i in quarter t scaled by the lagged total outstanding loans. The independent variable is a measure of P2P lending volume. In the first two columns, we use alternative model specifications. In column (1), we follow Kanagaretnam, Krishnan and Lobo (2010) to further control for beginning nonperforming loans ($NPL_{i,t-1}$), current net charge-offs ($CO_{i,t}$) and change in nonperforming loans ($\Delta NPL_{i,t}$). In column (2), we follow Basu, Vitanza, and Wang's (2020) specification to account for asymmetric loan loss provisioning. In columns (3)-(5), we use alternative measures of P2P lending. In columns (6)-(9), we use an alternative sample to test the main hypothesis. In columns (6) and (7), we exclude observations from Iowa and California, respectively. In column (8), we construct a bigger sample to include both single-state banks and multistate banks. All state-level variables of multistate banks, including the P2P lending measure ($LNP2P_{s,t-1}$), take the weighted average value, where the weighting scheme is based on the geographical distribution of bank deposits. In column (9), we exclude observations that may involve mergers and acquisition (M&A) as the growth rate of their non-loan assets exceeds 10%. All other variables are defined in Appendix A. All continuous variables are winsorized at the 1st and 99th percentiles. Constant terms are estimated but untabulated. The model includes bank fixed effects and year-quarter fixed effects; t-values, based on robust standard errors two-way clustered by bank and year-quarter, are reported in parentheses. ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively.

Table 4 Instrumental variable approach

Dep. Var. =	(1) $LNP2P_{s,t-1}$	(2) $LLP_{i,t}$
$\boldsymbol{LNP2P_{s,t-1}}$ (instrumented)		**0.0126***** **(3.59)**
$\boldsymbol{LICENSEQTR_{s,t-1}}$	**0.0011***** **(8.95)**	
$SIZE_{i,t-1}$	0.0082*** (5.60)	0.0012*** (6.64)
$EBP_{i,t}$	−0.1958*** (−4.64)	−0.0185** (−2.13)
$CAPR1_{i,t-1}$	−0.0070 (−1.10)	0.0014 (1.66)
$ALW_{i,t-1}$	0.2598*** (6.14)	−0.0079 (−1.08)
$HHI_{i,t-1}$	−0.0235** (−2.12)	−0.0032*** (−3.70)
$HETE_{i,t-1}$	−0.0073** (−2.72)	0.0029*** (7.84)
$\Delta LOAN_{i,t}$	−0.0021 (−0.80)	−0.0024*** (−4.02)
$\Delta GDP_{s,t}$	−0.0010 (−1.44)	0.0000 (0.50)
$\Delta UNEMP_{s,t}$	−0.0083** (−2.11)	0.0004*** (3.21)
$\Delta HPI_{s,t}$	−0.0050 (−0.05)	−0.0072** (−2.41)
$\Delta POP_{s,t}$	0.0141 (1.48)	−0.0006** (−2.63)
$GDP_{s,t-1}$	−0.0190 (−0.68)	0.0002 (0.34)
$UNEMP_{s,t-1}$	−0.0073*** (−6.48)	0.0002*** (4.04)
$HPI_{s,t-1}$	0.2651*** (14.88)	−0.0044*** (−3.15)
$POP_{s,t-1}$	0.0373*** (3.35)	−0.0016** (−2.40)
$AUTOD_{s,t-1}$	−0.1149*** (−6.65)	0.0036*** (3.16)
$CCD_{s,t-1}$	0.1985*** (7.92)	−0.0003 (−0.33)
$MORTD_{s,t-1}$	−0.0460* (−1.74)	0.0046*** (3.92)
$DELINQ_{s,t-1}$	−0.0051*** (−5.90)	0.0001*** (3.17)
Bank fixed effects	Yes	Yes
Year-quarter fixed effects	Yes	Yes
N	201,056	201,056
adj. R^2	0.831	0.340

This table presents the results of using the instrumental variable (IV) approach to address endogeneity concerns. We use as an IV the number of quarters since both LendingClub and Prosper obtained their license in a particular state. Column (1) presents the first-stage results, while column (2) presents the second-stage results. All variables are defined in Appendix A. All continuous variables are winsorized at the 1st and 99th percentiles. Constant terms are estimated but untabulated. The model includes bank fixed effects and year-quarter fixed effects; t-values, based on robust standard errors two-way clustered by bank and year-quarter, are reported in parentheses. ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively.

Table 5 Cross-sectional tests: the common-lending effect (H2)

Dep. Var. = $LLP_{i,t}$	(1) Level of consumer loans at t−1 ($CSLOAN_{i,t-1}$)	(2) Change in consumer loans from t−1 to t ($\Delta CSLOAN_{i,t}$)
$\boldsymbol{LNP2P_{s,t-1} \times HIGH}$	**0.0032***	**0.0011***
	(5.08)	**(4.34)**
$LNP2P_{s,t-1}$	0.0024***	0.0035***
	(3.40)	(4.88)
$HIGH$	−0.0000	−0.0001***
	(−0.44)	(−5.41)
$SIZE_{i,t-1}$	0.0013***	0.0014***
	(6.90)	(6.91)
$EBP_{i,t}$	−0.0197**	−0.0220**
	(−2.24)	(−2.44)
$CAPR1_{i,t-1}$	0.0013	0.0016*
	(1.51)	(1.91)
$ALW_{i,t-1}$	−0.0060	−0.0075
	(−0.84)	(−1.04)
$HHI_{i,t-1}$	−0.0031***	−0.0029***
	(−3.63)	(−3.50)
$HETE_{i,t-1}$	0.0027***	0.0029***
	(7.82)	(8.01)
$\Delta LOAN_{i,t}$	−0.0024***	−0.0026***
	(−4.01)	(−4.13)
$\Delta GDP_{s,t}$	−0.0000	−0.0000
	(−0.28)	(−0.41)
$\Delta UNEMP_{s,t}$	0.0003***	0.0003**
	(2.81)	(2.68)
$\Delta HPI_{s,t}$	−0.0073**	−0.0078**
	(−2.52)	(−2.71)
$\Delta POP_{s,t}$	−0.0005***	−0.0005***
	(−3.15)	(−3.01)
$GDP_{s,t-1}$	−0.0002	−0.0005
	(−0.24)	(−0.81)
$UNEMP_{s,t-1}$	0.0001***	0.0001**
	(2.75)	(2.65)
$HPI_{s,t-1}$	−0.0021***	−0.0019***
	(−3.08)	(−2.85)
$POP_{s,t-1}$	−0.0012*	−0.0011
	(−1.89)	(−1.63)
$AUTOD_{s,t-1}$	0.0026***	0.0025***
	(2.88)	(3.05)
$CCD_{s,t-1}$	0.0014**	0.0013*
	(2.08)	(1.95)
$MORTD_{s,t-1}$	0.0041***	0.0040***
	(4.29)	(3.90)
$DELINQ_{s,t-1}$	0.0000	0.0001
	(1.48)	(1.56)
Bank fixed effects	Yes	Yes
Year-quarter fixed effects	Yes	Yes
N	201,056	198,290
adj. R^2	0.344	0.347

This table presents the results of testing H2. The dependent variable is loan loss provisions ($LLP_{i,t}$), defined as the loan loss provisions of bank i in quarter t scaled by the lagged total outstanding loans. The independent variable is P2P lending ($LNP2P_{s,t-1}$), defined as the natural logarithm of 1 plus the state-quarter aggregate loan volumes (in billion US dollars) originated by LendingClub and Prosper during quarter t−1. To capture the extent of common lending, we use the level of consumer loans in quarter t−1 in column (1) and the change in consumer loans from quarter $t-1$ to quarter t in column (2). To ease the interpretation of the coefficient on the interaction term, we create an indicator variable, *HIGH*, that equals 1 for states whose partition variable is higher than the state-quarter median, and 0 otherwise. All other variables are defined in Appendix A. All continuous variables are winsorized at the 1st and 99th percentiles. Constant terms are estimated but untabulated. The model includes bank fixed effects and year-quarter fixed effects; t-values, based on robust standard errors two-way clustered by bank and year-quarter, are reported in parentheses. ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively.

Table 6 Cross-sectional tests: the overleveraged consumer effect (H3)

Dep. Var. = $LLP_{i,t}$	(1) State-level household debt delinquency rate at $t-1$ ($DELINQ_{s,t-1}$)	(2) Bank-level nonperforming consumer loans at $t-1$ ($NPL\_CSL_{i,t-1}$)
$\boldsymbol{LNP2P_{s,t-1} \times HIGH}$	**0.0018****	**0.0013****
	(2.53)	**(2.70)**
$LNP2P_{s,t-1}$	0.0021**	0.0035***
	(2.47)	(4.83)
$HIGH$	−0.0000	0.0001***
	(−0.53)	(6.49)
$SIZE_{i,t-1}$	0.0013***	0.0014***
	(6.84)	(6.91)
$EBP_{i,t}$	−0.0201**	−0.0215**
	(−2.26)	(−2.41)
$CAPR1_{i,t-1}$	0.0013	0.0013
	(1.58)	(1.66)
$ALW_{i,t-1}$	−0.0054	−0.0086
	(−0.75)	(−1.19)
$HHI_{i,t-1}$	−0.0030***	−0.0031***
	(−3.42)	(−3.75)
$HETE_{i,t-1}$	0.0028***	0.0029***
	(8.00)	(7.94)
$\Delta LOAN_{i,t}$	−0.0025***	−0.0027***
	(−4.02)	(−4.23)
$\Delta GDP_{s,t}$	−0.0000	−0.0000
	(−0.06)	(−0.23)
$\Delta UNEMP_{s,t}$	0.0003**	0.0003**
	(2.62)	(2.62)
$\Delta HPI_{s,t}$	−0.0076**	−0.0074**
	(−2.59)	(−2.58)
$\Delta POP_{s,t}$	−0.0005***	−0.0005***
	(−2.98)	(−3.00)
$GDP_{s,t-1}$	−0.0001	−0.0004
	(−0.16)	(−0.65)
$UNEMP_{s,t-1}$	0.0001**	0.0001**
	(2.49)	(2.71)
$HPI_{s,t-1}$	−0.0023***	−0.0020***
	(−3.96)	(−2.85)
$POP_{s,t-1}$	−0.0013*	−0.0012*
	(−1.94)	(−1.69)
$AUTOD_{s,t-1}$	0.0024**	0.0024***
	(2.67)	(2.96)
$CCD_{s,t-1}$	0.0013*	0.0014**
	(1.94)	(2.08)
$MORTD_{s,t-1}$	0.0049***	0.0039***
	(8.01)	(4.01)
$DELINQ_{s,t-1}$		0.0001
		(1.64)
Bank fixed effects	Yes	Yes
Year-quarter fixed effects	Yes	Yes
N	201,056	196,746
adj. R^2	0.344	0.343

This table presents the results of testing H3. The dependent variable is loan loss provisions ($LLP_{i,t}$), defined as the loan loss provisions of bank i in quarter t scaled by the lagged total outstanding loans. The independent variable is P2P lending ($LNP2P_{s,t-1}$), defined as the natural logarithm of 1 plus the state-quarter aggregate loan volumes (in billion US dollars) originated by LendingClub and Prosper during quarter $t-1$. In column (1), we use the overall delinquency rate as a proxy for the ex ante likelihood of banks having overleveraged borrowers. Specifically, the partition variable = the overall delinquency rate in state *s* for quarter $t-1$ = (auto debt per capita × auto debt delinquency rate + credit card debt per capita × credit card debt delinquency rate + mortgage debt per capita × mortgage debt delinquency rate)/(auto debt per capita + credit card debt per capita + mortgage debt per capita). In column (2), we use the nonperforming consumer loans in quarter $t-1$. To ease the interpretation of the coefficient on the interaction term, we create an indicator variable, *HIGH*, that equals 1 for states whose partition variable is higher than the quarter median, and 0 otherwise. All other variables are defined in Appendix A. All continuous variables are winsorized at the 1st and 99th percentiles. Constant terms are estimated but untabulated. The model includes bank fixed effects and year-quarter fixed effects; t-values, based on robust standard errors two-way clustered by bank and year-quarter, are reported in parentheses. ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively.

Table 7 Additional tests: components of P2P lending volume

Dep. Var. =	(1) $LLP_{i,t}$	(2) $LLP_{i,t}$
$LNP2P\_DC_{s,t-1}$	**0.0089***** **(3.24)**	
$LNP2P\_OP_{s,t-1}$	**−0.0176*** **(−1.75)**	
$LNP2P\_RT_{s,t-1}$		**0.0155***** **(4.65)**
$LNP2P\_IS_{s,t-1}$		**0.0018**** **(2.70)**
$SIZE_{i,t-1}$	0.0013*** (6.83)	0.0013*** (6.84)
$EBP_{i,t}$	−0.0200** (−2.26)	−0.0199** (−2.25)
$CAPR1_{i,t-1}$	0.0013 (1.57)	0.0013 (1.57)
$ALW_{i,t-1}$	−0.0055 (−0.77)	−0.0057 (−0.80)
$HHI_{i,t-1}$	−0.0031*** (−3.68)	−0.0031*** (−3.69)
$HETE_{i,t-1}$	0.0028*** (7.95)	0.0028*** (7.99)
$\Delta LOAN_{i,t}$	−0.0025*** (−4.01)	−0.0025*** (−4.03)
$\Delta GDP_{s,t}$	−0.0000 (−0.18)	−0.0000 (−0.14)
$\Delta UNEMP_{s,t}$	0.0003*** (2.87)	0.0003*** (3.13)
$\Delta HPI_{s,t}$	−0.0073** (−2.55)	−0.0084*** (−2.88)
$\Delta POP_{s,t}$	−0.0005*** (−3.22)	−0.0006*** (−3.53)
$GDP_{s,t-1}$	−0.0003 (−0.51)	−0.0004 (−0.55)
$UNEMP_{s,t-1}$	0.0001*** (2.80)	0.0001** (2.53)
$HPI_{s,t-1}$	−0.0019*** (−2.89)	−0.0021*** (−3.11)
$POP_{s,t-1}$	−0.0012* (−1.85)	−0.0013* (−1.98)
$AUTOD_{s,t-1}$	0.0025*** (2.82)	0.0029*** (3.16)
$CCD_{s,t-1}$	0.0015** (2.16)	0.0015** (2.16)
$MORTD_{s,t-1}$	0.0041*** (4.31)	0.0040*** (4.25)
$DELINQ_{s,t-1}$	0.0000 (1.47)	0.0000 (1.47)
N	201,056	201,056
adj. R^2	0.344	0.344
F-test for coefficient difference:	$LNP2P\_DC_{s,t-1} = LNP2P\_OP_{s,t-1}$	$LNP2P\_RT_{s,t-1} = LNP2P\_IS_{s,t-1}$
p-value:	0.0446**	0.0006***

This table presents the results of testing H3. The dependent variable is loan loss provisions ($LLP_{i,t}$), defined as the loan loss provisions of bank i in quarter t scaled by the lagged total outstanding loans. The independent variables of interest are the components of P2P lending volume. In column (1), we divide the total P2P lending volume into two components according to loan purpose: loans for debt consolidation ($LNP2P\_DC_{s,t-1}$) vs. loans for other purposes ($LNP2P\_OP_{s,t-1}$). In column (2), we divide the total P2P lending volume into two components according to lender type: loans funded by retail lenders ($LNP2P\_RT_{s,t-1}$) vs. loans funded by institutional lenders ($LNP2P\_IS_{s,t-1}$). All other variables are defined in Appendix A. All continuous variables are winsorized at the 1st and 99th percentiles. Constant terms are estimated but untabulated. The model includes bank fixed effects and year-quarter fixed effects; t-values, based on robust standard errors two-way clustered by bank and year-quarter, are reported in parentheses. ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively.

Table 8 Additional tests: the role of accounting discretion

Dep. Var. = $LLP_{i,t}$	(1) Earnings before provisions in quarter t ($EBP_{i,t}$)	(2) Regulatory capital ratio at the end of quarter $t-1$ ($CAPR1_{i,t-1}$)
$\boldsymbol{LNP2P_{s,t-1} \times HIGH}$	**0.0016*****	**0.0028*****
	(3.53)	**(5.03)**
$LNP2P_{s,t-1}$	0.0034***	0.0027***
	(4.92)	(3.84)
$HIGH$	0.0000	−0.0002***
	(0.46)	(−4.45)
$SIZE_{i,t-1}$	0.0012***	0.0012***
	(6.73)	(6.98)
$EBP_{i,t}$		−0.0202**
		(−2.22)
$CAPR1_{i,t-1}$	0.0014	
	(1.57)	
$ALW_{i,t-1}$	−0.0048	−0.0056
	(−0.69)	(−0.79)
$HHI_{i,t-1}$	−0.0032***	−0.0031***
	(−3.66)	(−3.63)
$HETE_{i,t-1}$	0.0028***	0.0027***
	(7.94)	(7.86)
$\Delta LOAN_{i,t}$	−0.0026***	−0.0023***
	(−4.04)	(−4.11)
$\Delta GDP_{s,t}$	−0.0000	−0.0000
	(−0.26)	(−0.26)
$\Delta UNEMP_{s,t}$	0.0003***	0.0003***
	(2.81)	(2.78)
$\Delta HPI_{s,t}$	−0.0073**	−0.0073**
	(−2.47)	(−2.49)
$\Delta POP_{s,t}$	−0.0005***	−0.0005***
	(−3.12)	(−3.13)
$GDP_{s,t-1}$	−0.0002	−0.0002
	(−0.28)	(−0.26)
$UNEMP_{s,t-1}$	0.0001***	0.0001**
	(2.87)	(2.71)
$HPI_{s,t-1}$	−0.0021***	−0.0020***
	(−3.03)	(−3.05)
$POP_{s,t-1}$	−0.0012*	−0.0012*
	(−1.95)	(−1.91)
$AUTOD_{s,t-1}$	0.0025***	0.0025***
	(2.84)	(2.86)
$CCD_{s,t-1}$	0.0014*	0.0014**
	(2.00)	(2.05)
$MORTD_{s,t-1}$	0.0042***	0.0042***
	(4.29)	(4.32)
$DELINQ_{s,t-1}$	0.0000	0.0000
	(1.43)	(1.44)
Bank fixed effects	Yes	Yes
Year-quarter fixed effects	Yes	Yes
N	201,056	201,056
adj. R^2	0.343	0.344

This table presents the results of exploring the role of accounting discretion. The dependent variable is loan loss provisions ($LLP_{i,t}$), defined as the loan loss provisions of bank i in quarter t scaled by the lagged total outstanding loans. The independent variable is P2P lending ($LNP2P_{s,t-1}$), defined as the natural logarithm of 1 plus the state-quarter aggregate loan volumes (in billion US dollars) originated by LendingClub and Prosper during quarter $t-1$. In column (1), we use earnings before provisions as a proxy for banks' capacity to accrue for loan losses. Specifically, the partition variable is calculated as bank *i*'s earnings before taxes and loan loss provisions in quarter *t*, scaled by the lagged total loans. In column (2), we use regulatory capital ratio as a proxy for banks' capacity to accrue for loan losses. Specifically, the partition variable is bank *i*'s tier 1 risk-based capital ratio at the beginning of quarter *t*. To ease the interpretation of the coefficient on the interaction term, we create an indicator variable, *HIGH*, that equals 1 for banks whose partition variable is higher than the state-quarter median, and 0 otherwise. All other variables are defined in Appendix A. All continuous variables are winsorized at the 1st and 99th percentiles. Constant terms are estimated but untabulated. The model includes bank fixed effects and year-quarter fixed effects; t-values, based on robust standard errors two-way clustered by bank and year-quarter, are reported in parentheses. ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively.

Table 9 Additional tests: the effect of P2P lending on banks' future charge-offs

Dep. Var. =	(1) $CO\_CSL_{i,t+1}$	(2) $CO\_TTL_{i,t+1}$
$\boldsymbol{LNP2P_{s,t-1}}$	**0.0019****	**0.0029*****
	(2.42)	**(4.67)**
$SIZE_{i,t-1}$	0.0009***	0.0013***
	(5.87)	(6.90)
$EBP_{i,t}$	0.0247***	−0.0015
	(4.01)	(−0.40)
$CAPR1_{i,t-1}$	−0.0014*	−0.0019***
	(−1.93)	(−4.29)
$ALW_{i,t-1}$	0.0369***	0.0904***
	(7.04)	(19.90)
$HHI_{i,t-1}$	−0.0015	−0.0015**
	(−1.52)	(−2.11)
$HETE_{i,t-1}$	0.0006**	0.0017***
	(2.46)	(5.95)
$\Delta LOAN_{i,t}$	−0.0014***	−0.0025***
	(−4.72)	(−8.37)
$\Delta GDP_{s,t}$	−0.0000	−0.0000
	(−0.49)	(−1.54)
$\Delta UNEMP_{s,t}$	0.0001	0.0002**
	(1.35)	(2.63)
$\Delta HPI_{s,t}$	−0.0050***	−0.0108**
	(−2.78)	(−2.51)
$\Delta POP_{s,t}$	−0.0003**	−0.0003**
	(−2.72)	(−2.15)
$GDP_{s,t-1}$	−0.0003	−0.0002
	(−0.59)	(−0.35)
$UNEMP_{s,t-1}$	0.0001***	0.0001***
	(3.15)	(3.08)
$HPI_{s,t-1}$	−0.0002	−0.0009**
	(−0.35)	(−2.43)
$POP_{s,t-1}$	0.0001	−0.0008
	(0.08)	(−1.46)
$AUTOD_{s,t-1}$	0.0018***	0.0013**
	(3.66)	(2.40)
$CCD_{s,t-1}$	0.0022***	0.0008
	(3.25)	(1.47)
$MORTD_{s,t-1}$	−0.0006	0.0020***
	(−1.02)	(2.86)
$DELINQ_{s,t-1}$	0.0001***	0.0001**
	(2.82)	(2.43)
Bank fixed effects	Yes	Yes
Year-quarter fixed effects	Yes	Yes
N	196,603	199,338
adj. R^2	0.191	0.344

This table presents the results of testing the effect of P2P lending on banks' future charge-offs. The dependent variable in column (1), $CO\_CSL_{i,t+1}$, is defined as bank i's net charge-offs of consumer loans in quarter t+1 scaled by the consumer loan balance in quarter t. The dependent variable in column (2), $CO\_TTL_{i,t+1}$, is defined as bank i's net charge-offs of total loans in quarter t+1 scaled by the total loans balance in quarter t. The independent variable is P2P lending ($LNP2P_{s,t-1}$), defined as the natural logarithm of 1 plus the state-quarter aggregate loan volumes (in billion US dollars) originated by LendingClub and Prosper during quarter $t-1$. All other variables are defined in Appendix A. All continuous variables are winsorized at the 1st and 99th percentiles. Constant terms are estimated but untabulated. The model includes bank fixed effects and year-quarter fixed effects; t-values, based on robust standard errors two-way clustered by bank and year-quarter, are reported in parentheses. ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively.