SPILLOVER EFFECT OF PEER-TO-PEER LENDING ON THE LOAN LOSSES OF COMMERCIAL BANKS

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

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CERTIFICATE OF ORIGINALITY

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Abstract

Financial technology (FinTech) companies play an increasingly important role in the financial system. I 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 the expected loan losses of the commercial banks within the state. If P2P lending provides borrowers with another source of funding to repay their bank loans, banks might report less expected loan losses. However, if P2P lending results in higher leveraged borrowers, banks might report more expected loan losses. Focusing on a large sample of US single-state banks during 2009-2017, I find that banks in states where P2P lending volume is higher report higher loan loss provisions. I also find that this positive relation is stronger for banks that have 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. In a supplementary test, I find evidence that P2P lending is associated with higher future loan charge-offs, which capture realized loan losses. Overall, my study offers new insight into the interaction between FinTech firms and traditional financial institutions.

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

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1. 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. To better understand this rising force, a nascent literature makes FinTech development its focus. The 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 et al., 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). An important reason for studying this interaction is that a borrower can typically choose to borrow from a bank, from a P2P lending platform, or from both. Hence, when P2P lending develops in a region, one might expect banks in that region to 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 spiraling effect that impacts other lenders, and it might even endanger the financial system.

In this paper, to gain a better understanding of the spillover effect of P2P lending on the traditional banking sector, I examine 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 meant to accrue for expected loan losses and are the key component of total accruals in the banking industry (Beatty and

[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).

Liao, 2011, 2014). Loan loss provisions provide a timely indicator of a bank's expectation of loan losses when it receives private information, e.g., notification of borrowers' financial difficulties and nonrepayment of existing loans. Hence, I rely on loan loss provisions to examine the impact of P2P lending on the loan losses of commercial banks and I argue that the relation between P2P lending and banks' loan losses is an empirical issue. [2]

On one hand, 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 FinTech application, P2P lending platforms provide an additional, easy source of funding for individuals and households. The funding obtained from P2P lending platforms could be directly used to repay borrowers' bank debt. In fact, most borrowers use P2P lending to refinance expensive bank debt (Balyuk, 2019). Given the easiness and convenience of applying for P2P loans, this additional funding source can also be used to manage a short-term cash flow gap. The availability of this additional funding source, possibly even at a lower debt financing cost, would reduce the incidence of personal bankruptcy (Jagtiani and Lemieux, 2018; Balyuk, 2019; 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

[2] In other word, I use loan loss provisions as a measure of loan losses. Although it would be interesting to examine the effect of P2P lending on a bank's specific type of loan loss, I cannot directly test it because data on specific types of loan losses is unavailable. The available loan loss provisions data aggregate a bank's loan losses from all types of outstanding loans. Throughout the paper, the terms "loan loss provisions", "reported loan losses" and "expected loan losses" are used interchangeably.

[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 funding borrowed on P2P platforms to repay bank debt could be a feasible, if temporary, solution. However, this solution can also be used strategically. For example, making a repayment allows borrowers to borrow money from the revolving account again. This could actually exacerbate borrowers' overleverage problem because easy P2P funding helps conceal repayment problems. I discuss this issue in greater depth in the hypothesis development section.

a negative relation between P2P lending and commercial banks' loan losses.

On the other hand, the borrower overleverage channel predicts a positive relation between P2P lending and banks' loan losses. An overleveraging effect might occur when borrowers have 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). It is tempting to borrow too much, especially when borrowing becomes easier and more convenient. Banks' existing borrowers may continue to borrow money from P2P platforms once these platforms become available for them. In addition, facing competition from P2P platforms, banks may compromise their lending standards to issue new loans to lower quality borrowers. Either ways, as the local P2P lending market develops, banks' individual/household borrowers would become more leveraged. The overleverage 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 luring borrowers into a debt trap (Domowitz and Sartain, 1999; Gross and Souleles, 2002; White, 2007; Livshits, MacGee and Tertile, 2010, 2016; Chava, Paradkar and Zhang, 2019). To the extent that P2P lending leads to overleveraged borrowers, one might expect banks to suffer more loan losses. Alternately, I might find no relation between P2P lending and loan losses if bank managers fail to incorporate the impact of P2P lending into their loan loss provisions. Taken together, 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, I construct a comprehensive sample of single-state banks' quarterly observations from 2009 to 2017. To measure each bank's exposure to P2P lending, I extract loan-level data from the top two US P2P platforms, LendingClub and Prosper. I then aggregate the originated loan volumes by state-quarter. I test the main hypothesis by regressing loan loss provisions on the aggregated

P2P lending volume for each bank's operating state. In the regression model, I also control for a series of bank and state level factors, as well as bank and quarter fixed effects. Consistent with P2P lending inducing overleverage on the borrower's part, I 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% when the P2P lending variable moves from its 25th to its 75th percentile. I construct instrumental variables based on state-level regulation and the IV-2SLS estimation suggests a causal effect of P2P lending on banks' loan losses. My 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 overleverage channel, my subsequent cross-section tests and additional tests focus on providing more support to this channel. First, I conduct two cross-sectional tests to provide corroborative evidence to the overleverage channel. My first cross-sectional test exploits the variability of 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 more extensive because P2P platforms target individual/household borrowers. Consistent with this expectation, I find that the positive relation between P2P lending and loan loss provisions is stronger for banks that have a higher percentage of consumer loan balance and for banks that have a larger increase in consumer loans.

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

Next, I conduct several additional tests to offer further insights on the effect of P2P lending on loan losses. First, I explore whether different components of the P2P lending volume have different effect on banks' loan losses. I divide the P2P lending volume into different components according to loan purpose (i.e., loans for debt consolidation vs. loans for other purposes) or lender types (loan volume funded by retail lenders vs. institutional lenders). I find that my main finding is likely to be driven by those 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. I 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.

I also explore whether banks' capacity to make loan loss provisions moderates the relation between P2P lending and expected loan losses. Given that higher capacity banks are subject to fewer constraints in accruing for loan losses, I expect that, the positive effects of P2P lending on loan loss provisions will be more pronounced for such banks. Consistent with my expectation, I 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, I 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 according to bank managers' expectations, 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 can validate the underlying argument of my central hypothesis and offer evidence to further support the overleverage 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, I find a significantly positive relation between P2P lending and banks' future quarter charge-offs.

This study makes two contributions to the literature. First, I 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, Siegel and Young, 2012; Zhang and Liu, 2012; Lin, Prabhala and Viswanathan, 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, Cornaggia and Gurun, 2017; Cornaggia, Wolfe and Yoo, 2018; Tang, 2019; Chava, Paradkar and Zhang, 2019). Through the lens of P2P lending, I study the spillover effects of FinTech development on traditional financial institutions. To the best of my knowledge, I am the first to link P2P lending with traditional banks' loan losses via the overleverage 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 when estimating 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 et al., 2017; Dou, Ryan and Zou, 2018; Nicoletti, 2018). I 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, my study may also have policy and regulatory implications.

The rest of this paper is organized as follows. Section 2 introduces the background and develops the hypotheses. Section 3 describes the data and research design. The main findings and robustness tests are reported in Section 4. Section 5 discusses the cross-sectional analyses. Additional analyses are provided in Section 6 before conclusions are drawn in Section 7.

2. Background and hypotheses development

2.1 The P2P lending business

P2P lending is the implementation of crowdfunding in the household finance arena and 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 money and those who are willing to lend. Under the P2P lending business model, the platform serves as an information provider, i.e., 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, e.g., they bear the loss if the borrower

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

defaults.

Individuals who want to borrow money on P2P lending platforms can register as a borrower and submit an application online. Along with the loan description, borrowers are required to report certain key information, e.g., employment status, annual income, 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] Taking advantage of advanced computer technology, this evaluation process takes only a few seconds before the platform provides the applicant with various loan options for which the applicant qualifies, including the loan term, loan amount and interest rate. After the applicant selects one of the options 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, a loan is issued to the applicant by the issuing bank, which works 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., the borrower payment dependent notes) to the investors who are committed to funding the loan. Figure 1 depicts the loan issuance mechanism of P2P lending platforms. Over the whole course 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 chase delinquent borrowers for overdue debt and they regularly report delinquent borrowers to

[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.

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, other platforms have emerged in the market, e.g., LendingClub, Upstart, Funding Circle, 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% that year from just 5% 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% and 22% of the US P2P lending market.[8] These two platforms are in fact also the top two platforms worldwide.[9]

2.2 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, it may also have a substantial impact on the financial system as a whole. Although P2P lending platforms and traditional banks have different business models,

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[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-.

[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/.

they serve nearly identical functions for potential borrowers, particularly individuals and households. 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, Wolfe and Yoo, 2018). Complementing this line of literature, I focus on the spillover effect of P2P lending on banks' loan losses. I argue that the relation between P2P lending and banks' loan losses is an empirical question.

On the one hand, 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] It is reasonable to use P2P funding for debt consolidation, especially when banks charge a relatively higher interest rate. P2P funding could also reasonably be used to manage a short-term cash flow gap. 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/her home due to a short-term cash flow problem. Accordingly, banks may well perceive the additional funding source available on P2P lending platforms as arguably increasing borrowers' ability to repay their bank loans and reducing the incidence of personal bankruptcy (Jagtiani and Lemieux, 2018; Balyuk, 2019; 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

[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.

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

On the other hand, the borrower overleverage 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). "Easy money is the great cause of over-borrowing" (Fisher, 1933). It is tempting to borrow too much, especially when FinTech development has made it easier and more convenient to borrow. To the extent that existing borrowers of 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 overleverage problem and eventually personal bankruptcy (Fisher, 1933; Domowitz and Sartain, 1999; Gross and Souleles, 2002; White, 2007; Livshits, MacGee and Tertile, 2010, 2016; Chava, Paradkar and Zhang, 2019). In light of the overleverage issues caused by P2P lending, banks are expected to suffer more loan losses.

Under the aforementioned overleveraging effect of P2P lending on banks' existing borrowers, I implicitly assume that banks face a challenge in dealing with such 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.

Several reasons support this assumption. First, banks may have difficulty in identifying borrowers who are ex ante more inclined 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 overleverage 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 is not restricted to the unsecured personal loan market even though the P2P lending platforms are aimed at this niche market. Instead, this effect also applies to banks' general individual/household borrowers, regardless of the loan purpose and collateral condition. For example, overleverage due to excessive consumer loans from P2P lending platforms can reduce borrowers' ability to repay their bank mortgage loans.

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, Wolfe and Yoo, 2018; Tang, 2019). For example, Cornaggia, Wolfe and Yoo (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 hence reduces charter value, which in turn creates incentives for excessive bank risk-taking (Keeley, 1990; Bushman, Hendricks and Williams, 2016). Specifically, banks may issue new loans to extant, already overleveraged borrowers. Alternatively, they may reach out to potential borrowers of

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

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.

P2P lending may contribute to borrowers' overleverage problem in another way. As discussed earlier, borrowers may use P2P funding to repay their bank debt and credit card balances. However, after repaying the bank, borrowers might again borrow money from the bank, particularly through revolving accounts such as credit cards (Chava, Paradkar and Zhang, 2019). Chava, Paradkar and Zhang (2019) document that P2P borrowers' credit card balances decline dramatically immediately after the P2P loan origination. More importantly, they also find that the credit card balances quickly revert to the earlier level and that the borrowers then become even higher 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—an overleverage 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 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 ways, banks' individual/household borrowers will become more leveraged. This borrower overleverage channel predicts a positive relation between P2P lending and banks' loan losses. While the bank loan repayment channel predicts the opposite and creates tension to this hypothesis, prior literature shows that borrowers can eventually become overleveraged even though the borrowed P2P funding is used to repay their bank debt. All in all, I predict that banks will suffer more loan losses as the local P2P lending market becomes more developed. I 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]

2.3 Cross-sectional variation in the effects of P2P lending on banks' loan losses

Next, I 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 to the borrower overleverage channel through which P2P lending can increase banks' loan losses.

First, I focus on a bank's exposure to the consumer loan market. P2P lending platforms target individual and household borrowers, so these types of borrowers of banks are likely to be affected by P2P lending. In keeping with the overleveraging effect of P2P lending on banks' existing borrowers, banks that have more extensively participated in 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, Hendricks and Williams, 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. Taken together, I expect the positive association between P2P lending and loan losses to be stronger for banks with greater exposure to the consumer loan market. I 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, I focus on the ex ante leverage of consumers who borrow money from banks. Consumers with higher leverage are more likely to have difficulty in 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 higher leverage, once the additional loans obtained from P2P platforms are included, these debt-ridden bank borrowers are more likely to reach the default threshold. In contrast, the additional funding from P2P lending platforms may not contribute much, if any, to the overleveraging problem if a bank's borrowers have relatively lower leverage because they are probably still capable of repaying the increased level of debt. Accordingly, I expect the positive association between P2P lending and banks' loan losses to be stronger for banks whose consumer borrowers are higher leveraged. I 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.

3. Data and research design

3.1 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, I retrieve detailed loan-level data from the top two P2P lending platforms in the US, LendingClub and Prosper.[13] LendingClub started in 2007 and went public in 2014. It is now the market leader, originating, as of June 2019, loans amounting to $50 billion. 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, etc. To avoid confounding effects during the

[13] 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 is available for its users to download at https://www.prosper.com/investor/marketplace#/download.

recent economic recession, defined by NBER as 2007Q4-2009Q2, my 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.[14] Consistent with Balyuk and Davydenko's (2019) observation, loan volume recovered quickly after the temporary drop sparked by the crisis.

To link the P2P lending data to each commercial bank, I 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.[15] Regulators impose restrictions on both borrower and investor sides, 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, Wolfe and Yoo, 2018). It is this state-level regulation and the timing difference in obtaining the state licenses that create the 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, and the accumulated loan volumes were $1,087 and $403 million, respectively.

Specifically, I aggregate the loan amount by state (based on borrower location) and quarter (based on loan origination date). For each state-quarter, I first obtain the raw value of the aggregated P2P lending volume, which includes all loans originated through LendingClub and Prosper in the quarter and the state. To capture banks' P2P lending exposure, I define the

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

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

main P2P measure ($LNP2P_{s,t-1}$) as the natural logarithm of 1 plus the aggregated P2P loan origination volume during quarter *t-1*.[16]

To provide some stylized facts, I also aggregate the loan volume according to other classifications. First, I classify the total loan volume during the whole sample period by loan purpose as reported by the borrowers themselves.[17] 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, I divide all individual loans in my 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, respectively, for individual and institutional investors. While individual investors can only provide funding via the fractional pool, institutional investors can only lend money via the whole pool.[18] As shown in Figure 6, institutional investors in both platforms now dominate supply-side funding.

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

My study focuses on US commercial banks. I extract bank-level data from call reports filed with bank regulators.[19] Call reports contain quarterly financial data for each US bank, which I use to construct a series of bank-level variables. My identification strategy exploits

[16] As a robustness check, I also define a scaled P2P measure as the raw value of the aggregated P2P lending volume scaled by the state population and find qualitatively similar results. The state population is arguably an appropriate scaler because in the early years of the sample period, both the demand and supply of P2P funding come mainly from individuals. Hence a state with a larger population is naturally expected to generate a larger P2P lending volume.

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

[18] 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.

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

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 my analyses, I restrict my sample to single-state banks, i.e., banks that operate geographically within the borders of a specific state.[20] To identify single-state banks, I rely on the FDIC's Summary of Deposits (SOD) database. The SOD database gives the results of the annual survey of branch office deposits as of June 30 for all FDIC-insured institutions. Specifically, I classify a bank as a single-state bank if its deposits are from branches located in the same state. I also utilize the SOD data to construct a competition measure of the banking industry at the state level.

Finally, I 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, I obtain my 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.

3.2 Empirical model

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

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

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

In Equation (1), the unit of analysis is the bank-quarter observation. I use loan loss provisions reported in income statements to measure banks' loan losses. In nature, loan loss provisions capture bank managers' expectation of 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.[21] As described in the previous section, this variable measures the P2P lending exposure of banks operating in state *s* at quarter *t-1*. Therefore, my focus is the regression coefficient on $LNP2P_{s,t-1}$, i.e., β_1. In my central hypothesis, I argue that P2P lending could induce bank borrowers' overleverage problem, thus resulting in a higher repayment risk. Consistent with this prediction, I 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, Hendricks and Williams, 2016; Hribar et al., 2017; Dou, Ryan and Zou, 2018), I include a series of bank-level control variables.[22] First, I control for lagged bank size ($SIZE_{i,t-1}$), as it is a common control variable in the accounting

[21] I take the natural logarithm but do not scale the raw aggregated lending volume for two reasons. First of all, the baseline model includes a set of state-level time variant variables and also includes bank fixed effects which subsume state fixed effects. Therefore, the state size effect is well accounted for. Another reason is that there is no natural scaler and its choice may be arbitrary; hence one might suspect that my results could be driven by the arbitrary scaling effect.

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

and finance literature. Another reason the banking literature controls for size is that bank size is a commonly used threshold for closer regulatory scrutiny. To address earnings management and regulatory capital management incentives, I control for earnings before loan loss provisions ($EBP_{i,t}$) and the lagged tier 1 risk-based capital ratio ($CAPR1_{i,t-1}$). According to the process of 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, I also control for lagged loan loss allowances ($ALW_{i,t-1}$). Finally, I 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 my identification strategy relies on the variation in P2P lending across states and quarters, there might be some omitted state-quarter-level variables. Such macroeconomic variables can directly affect banks' loan loss provisions and/or P2P lending activities. I address this issue by including a variety of state-level variables. First, I control for several macroeconomic indicators commonly used in the banking literature, including the level of and change in state-level per capita GDP ($GDP_{s,t-1}$, $\Delta GDP_{s,t}$), 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, I follow Butler et al. (2017) and Cornaggia, Wolfe and Yoo (2018) to control for the household debt level and credit quality. Specifically, I 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.

I summarize the variable definitions in Appendix A. To reduce the influence of outliers, all continuous variables are winsorized at the 1% and 99% levels of their respective distributions. Finally, I 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 me to control for nationwide time-variant economic conditions. I use robust standard errors two-way clustered by bank and quarter to address the issue of heteroscedasticity and within-bank serial correlation in the error terms (Petersen, 2009; Gow et al., 2010).

3.3 Descriptive statistics

Table 1 presents the mean, standard deviation, median and the 25th and 75th percentile values of the variables used in my main regression. My 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 my sample is 0.12% (0.04%) of the lagged outstanding loans. Consistent with recent studies such as Hribar et al. (2017), I also note that over 25% of the bank-quarter observations are with 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, Ryan and Zou, 2018; Cornaggia, Wolfe and Yoo, 2018).

[Insert Table 1 Here]

4. Empirical results

4.1 P2P lending and banks' loan losses

In this section, I test my central hypothesis (H1). From bank borrowers' perspective, P2P lending platforms provide another source of funding that is relatively easy and convenient to obtain. I argue that on 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. Using money borrowed on a P2P platform to repay bank debt could indicate the borrower is overleveraged. Therefore, I 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, I 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.

I start my 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. My baseline results in Column (2) show that the coefficient on $LNP2P_{s,t-1}$ is 0.0040, which is statistically significant at the 1% 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 bank managers expect higher future loan losses as a result of overleveraged borrowers. Moreover, the magnitude of the regression coefficient is economically significant. Loan loss provisions increase by 9.63% when $LNP2P_{s,t-1}$ moves from its 25th to its 75th percentile.[23] Given that the P2P lending market is still growing steadily, this magnitude is considerable.[24]

[23] 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%.

[24] The P2P lending market is expected to expand at a CAGR of 4.95% during the forecast period from 2019 to 2025. See: https://www.marketwatch.com/press-release/p2p-lending-market-expected-to-expand-with-a-cagr-of-

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, Hendricks and Williams, 2016; Hribar et al., 2017; Dou, Ryan and Zou, 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 the 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.[25]

[Insert Table 2 Here]

4.2 Robustness checks

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

In my baseline model, I do not control for variables related to loan charge-offs and nonperforming loans. On one hand, my study is different from prior literature that aims to derive abnormal loan loss provisions. Instead, the purpose of my study is to investigate whether and how P2P lending affects banks' loan losses. On the other hand, 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, I check whether my results are sensitive to these additional control variables.

495-during-the-forecast-period-2019-2025-2019-07-31.

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

First, I 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 the change in nonperforming loans ($\Delta NPL_{i,t}$). Second, I follow Basu, Vitanza and Wang's (2020) suggestion 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 of the negative change 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 regression model. Table 3 Column (1) and (2) show that the coefficients on $LNP2P_{s,t-1}$ are significantly positive, with t-values of 5.02 and 5.24, respectively.[26]

Next, I check whether my results are sensitive to several alternative P2P measures. In my baseline regression, I use the main P2P measure which is defined as the natural logarithm of 1 plus the aggregated P2P loan origination volume during quarter *t-1*. As robustness checks, I propose three alternative P2P measures. First, I define a scaled P2P measure ($P2PPOP_{s,t-1}$) as the raw value of the aggregated P2P lending volume scaled by the state population which is arguably a reasonable scaler given that P2P platforms target individual borrowers. Besides P2P lending volume which is a flow measure, I also consider using P2P lending balance which is a stock measure. The balance-based P2P measure ($P2PBAL_{s,t-1}$) is defined as the aggregated P2P loan balance scaled by the state population. The third alternative measure ($P2PNPL_{s,t-1}$) is defined as the percentage of non-performing P2P loans divided by the outstanding P2P loans.[27] The third measure has closer ties to the spillover effects than do the first two measures: P2P loan repayment problems can create problems for bank loans. As shown in Table 3 Columns (3)-(5), focusing on these alternative P2P measures, I continue to

[26] Consistent with the over-controlling concern, the magnitude of the regression coefficient is smaller than the baseline results. This over-controlled magnitude seems to represent the lower bound of the economic significance: loan loss provisions increase by 4.82% (=(0.0020 × (0.0297-0.0008))/0.0012) when $LNP2P_{s,t-1}$ moves from its 25th to its 75th percentile.

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

find a significantly positive relation between P2P lending and banks' loan losses.

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

In addition, I conduct another robustness check in which I take into account multistate banks. To accurately measure banks' P2P lending exposure at the state level, I restrict my sample in the baseline analysis to single-state banks. However, excluding multistate banks, which are typically larger in size, may decrease the generalizability of my main finding. Because P2P lending volume is measured at the state level, I need a 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, I 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, I 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. Table 3, Column (8) presents the regression results for this bigger sample. Again, I continue to find a significantly positive relation between P2P lending and banks' expected loan losses. Specifically, the regression coefficient on $LNP2P_{s,t-1}$ is 0.0039, which is statistically significant at the 1% level (t-value = 5.72). Therefore, my baseline results are robust to this alternative sample that includes multistate banks.

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

[Insert Table 3 Here]

4.3 Instrumental variable approach to address endogeneity concerns

The variation in P2P lending volume is largely driven by state-level regulation, i.e., P2P platforms must obtain a license for a particular state before they operate in that state. In addition, it is less likely that P2P lending activities at the state level are endogenously determined by individual commercial banks. Therefore, my baseline results are unlikely to be driven by either selection bias or reverse causality. In an effort to mitigate the omitted variable issue, in the baseline model, I have included a series of state-level controls, bank fixed effects and year-quarter fixed effects. Nonetheless, my research design may not have adequately controlled for factors that influence both P2P lending activities and banks' loan loss provisions.

In this section, I take the instrumental variable (IV) approach to address endogeneity concerns due to omitted variables. 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 their business in some states later than in others. I exploit this variation in the time 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, it is obvious that the status and history of the state-level license have a significant impact on the P2P lending volume within that state.

I obtain the state-level license status from the 10-Ks that LendingClub and Prosper filed with the 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.” By comparing these two consecutive years’ descriptions, it is clear that LendingClub obtained new licenses for Kansas and North Carolina. I 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, I 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 had 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 my sample period (2009Q3-2017Q4).

I construct an IV based on the license status of LendingClub and Prosper.[29] Specifically,

[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 my sample period, LendingClub dominated the P2P lending market, capturing over 70% 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 I construct the IV solely based on the license status of LendingClub.

I 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, I present the IV-2SLS estimation. Column (1) presents the 1st stage results while Column (2) presents the 2nd stage results. In Column (1), I find that the IV is significantly associated with the P2P lending volume, with a t-value of 8.95. In Column (2), the 2nd stage results show that the coefficient on the instrumented $LNP2P_{s,t-1}$ is positive and statistically significant at the 1% 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]

5. Cross-sectional analyses

Because the empirical evidence shows that the dominant effect appears to be related to the overleverage channel, my subsequent tests focus on providing more support to this channel. In this section, I conduct two cross-sectional tests to shed light on the overleverage channel through which P2P lending can affect banks' loan losses.

5.1 The common-lending effect

My baseline results show that banks report more loan losses if they operate in a state 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 bank managers' expectation of future loan losses. In line with this channel, I 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, I 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.

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

To test this prediction, I rely on the customer base overlap between traditional banks and P2P lending platforms to measure banks' 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, banks with more individual/household borrowers would arguably be more severely affected. Operationally, I first use as the partition variable the level of consumer loans ($CSLOAN_{i,t-1}$), calculated as the percentage of outstanding consumer loans out of total loans, both lagged by one quarter. I 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, I create a dummy 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), I show the results using the level of consumer loan at quarter t-1 as the partition variable. The coefficient on the interaction term, $LNP2P_{s,t-1} \times HIGH$ is significantly positive. This 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), I 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 my hypothesis. Taken together, using the level of and the change in consumer loans to capture banks' exposure to the consumer loan market, I provide evidence that the effect of P2P lending on loan losses is stronger when banks have greater exposure to the consumer loan market. This common-lending effect corroborates the overleverage channel through which P2P lending can affect banks' loan losses.

[Insert Table 5 Here]

5.2 The overleveraged consumer effect

My 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 in repaying the banks, especially when the competitors (i.e., the P2P platforms) can make these consumers even more leveraged. When bank borrowers already have higher leverage, once the additional funding obtained from P2P platforms is included, these borrower are more likely to reach the default threshold. 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, I therefore hypothesize that the effect of P2P lending on loan losses will be stronger for banks whose consumer borrowers are already higher leveraged.

To test this prediction, I first use the extent of ex ante overleverage at the state level to capture the likelihood that local banks' borrowers are overleveraged. The basic idea is that individuals who are higher leveraged are more likely to be overleveraged if they also borrow from a P2P lending platform. Specifically, I 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). I 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, I create a dummy 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), I show the results using the state level household delinquency rate as the partition variable. The coefficient on the interaction term, $LNP2P_{s,t-1}$ × *HIGH* is significantly positive. This 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), I show the results using the lagged non-performing consumer loans as the partition variable. Again, the significantly positive coefficient on the interaction term supports my hypothesis. Taken together, these two distinct measures, which I 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 to the overleverage channel in my main hypothesis.

[Insert Table 6 Here]

6. Additional analyses

6.1 Components of P2P lending volume

In this section, I explore whether different components of the P2P lending volume have different effect on banks' loan losses. This is a unique and interesting analysis 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. I divide the P2P lending volume into two components: i) loans for debt consolidation ($LNP2P\_DC_{s,t-1}$), e.g., 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, etc. I also divide the P2P lending volume according to lender type. For each loan in the P2P lending data, I can identify if the loan is funded by retail lenders or institutional lenders. Accordingly, I 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, I put both components into the regression model. In Table 7 Column (1), I include $LNP2P\_DC_{s,t-1}$ and $LNP2P\_OP_{s,t-1}$ to test if the loan purpose matters. I find that the coefficient on $LNP2P\_DC_{s,t-1}$ is positive and statistically significant at the 1% level while the coefficient on $LNP2P\_OP_{s,t-1}$ is negative and statistically significant at the 10% level. The test for coefficient difference shows that the coefficient on debt consolidation loans ($LNP2P\_DC_{s,t-1}$) is significantly larger thus my main finding is likely driven by loans borrowed for debt consolidation purpose. This is consistent with my intuition that individuals on the verge of default are more likely to borrow money from P2P platforms to repay their bank debt.

In Table 7 Column (2), I include $LNP2P\_RT_{s,t-1}$ and $LNP2P\_IS_{s,t-1}$ to test if the lender type matters. I find that the coefficients on both $LNP2P\_RT_{s,t-1}$ and $LNP2P\_IS_{s,t-1}$ are significantly positive. The test for coefficient difference shows that the coefficient on loans funded by institutional lenders ($LNP2P\_RT_{s,t-1}$) is significantly smaller, suggesting that institutional lenders have higher screening ability and maintain a higher lending standard. Thus the institutional loan volume has smaller spillover effects on banks' loan losses.

[Insert Table 7 Here]

6.2 Exploring the role of accounting discretion

Next, I 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. Lower capacity banks may not be able to make sufficient loan loss provisions in response to their borrowers' becoming overleveraged due to P2P borrowing. Therefore, I 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, I divide my sample into higher-capacity and lower-capacity banks based on their earnings before loan loss provisions. Loan loss provisions decrease banks' net earnings, i.e., earnings after tax and loan loss provisions. As a result, 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, I also divide banks into two groups based on their regulatory capital ratio. Capital adequacy is the most prominent aspect of banking regulation. To reduce the risk of losing their valuable charter in case of failure, banks typically operate well above the required minimum capital ratio (Elizalde and Repullo, 2007). Regulators check at random whether banks are in compliance with the capital requirement (Repullo and Suarez, 2013). 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, I create a dummy 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. I then include in the regression model the interaction term between this dummy variable and the P2P lending volume.

Table 8 presents the results. In Column (1), I show the results when I measure capacity 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 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), I 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, I continue to find a significantly positive coefficient on the interaction term. Taken together, measuring banks' capacity to make loan loss provisions from two different perspectives yields consistent evidence 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]

6.3 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' expected loan losses. The central argument is that individuals borrowing on P2P platforms are likely to be overleveraged. Bank managers expect this overleveraging and, therefore, report more loan losses. While loan loss provisions capture bank managers' expectations, 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, I formally test whether P2P lending is associated with future realized loan losses. This test can validate my central argument and provide confirmation of the overleverage 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, I run the following OLS model:

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

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, I am also interested in the overall effect of P2P lending on banks' total charge-offs. Therefore, I use the total charge-offs ($CO_{i,t+1}$) as an alternative dependent variable. I focus on the coefficient on the P2P lending variable ($LNP2P_{s,t-1}$), i.e., β_1. A significantly positive β_1 would validate the proposed overleverage channel.

Table 9 presents the results. Column (1) shows the results of using future-one-quarter charge-offs of consumer loans as the dependent variable while Column (2) changes the dependent variable to 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 that P2P lending will have on future loan losses. Put differently, this additional test on future charge-offs provides direct evidence that my main results are driven by the borrowers' deteriorating condition rather than bank managers' behavioral bias. This deterioration in the borrowers' condition is in keeping with the overleverage channel proposed in my main hypothesis.

[Insert Table 9 Here]

7. Conclusion

In this paper, I investigate the relation between P2P lending and traditional banks' loan losses. Using a sample of single-state banks' quarterly observations from 2009 to 2017, I document that banks' expected loan losses increase as P2P lending booms. This main finding is statistically and economically significant. Results from the instrumental variable approach suggest a causal effect of P2P lending on banks' loan losses. I 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 higher 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, I provide further insights by showing that it is the P2P loans for debt consolidation purpose that drive my main finding. I 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, I further justify the overleverage channel by showing directly that P2P lending is positively associated with banks' future charge-offs, i.e., confirmed borrowers' defaults.

My study adds to the banking literature by documenting a new determinant of loan loss provisions. More importantly, my 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, I am 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

Variable	Definition	Data Source
State level P2P lending variables:		
$LNP2P_{s,t-1}$	Natural logarithm of 1 plus the state-quarter aggregated loan volumes (in $B) originated by LendingClub and Prosper during quarter t-1.	LendingClub and Prosper
$P2PPOP_{s,t-1}$	The state-quarter aggregated LendingClub and Prosper loan volumes during quarter t-1 scaled by the state population.	LendingClub and Prosper
$P2PBAL_{s,t-1}$	The state-quarter aggregated outstanding LendingClub loan balance at the end of quarter t-1 scaled by the state population.	LendingClub
$P2PNPL_{s,t-1}$	The state-quarter aggregated non-performing LendingClub loans scaled by the outstanding loan balance at the end of quarter t-1.	LendingClub
$LNP2P\_DC_{s,t-1}$	Natural logarithm of 1 plus the state-quarter aggregated loan volumes (in $B) for debt consolidation purpose during quarter t-1.	LendingClub and Prosper
$LNP2P\_OP_{s,t-1}$	Natural logarithm of 1 plus the state-quarter aggregated loan volumes (in $B) for other purpose during quarter t-1.	LendingClub and Prosper
$LNP2P\_RT_{s,t-1}$	Natural logarithm of 1 plus the state-quarter aggregated loan volumes (in $B) funded by retail lenders during quarter t-1.	LendingClub and Prosper
$LNP2P\_IS_{s,t-1}$	Natural logarithm of 1 plus the state-quarter aggregated loan volumes (in $B) 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 the 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 deposits distribution 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
$\Delta LOAN_{i,t}$	The change in total loans from quarter t-1 to quarter t scaled by the total loans in quarter t-1.	Call reports
$NPL_{i,t-1}$	Non-performing 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 the total loans in quarter t-1.	Call reports
$\Delta NPL_{i,t}$	The change in nonperforming loans from quarter t-1 to quarter t	Call reports

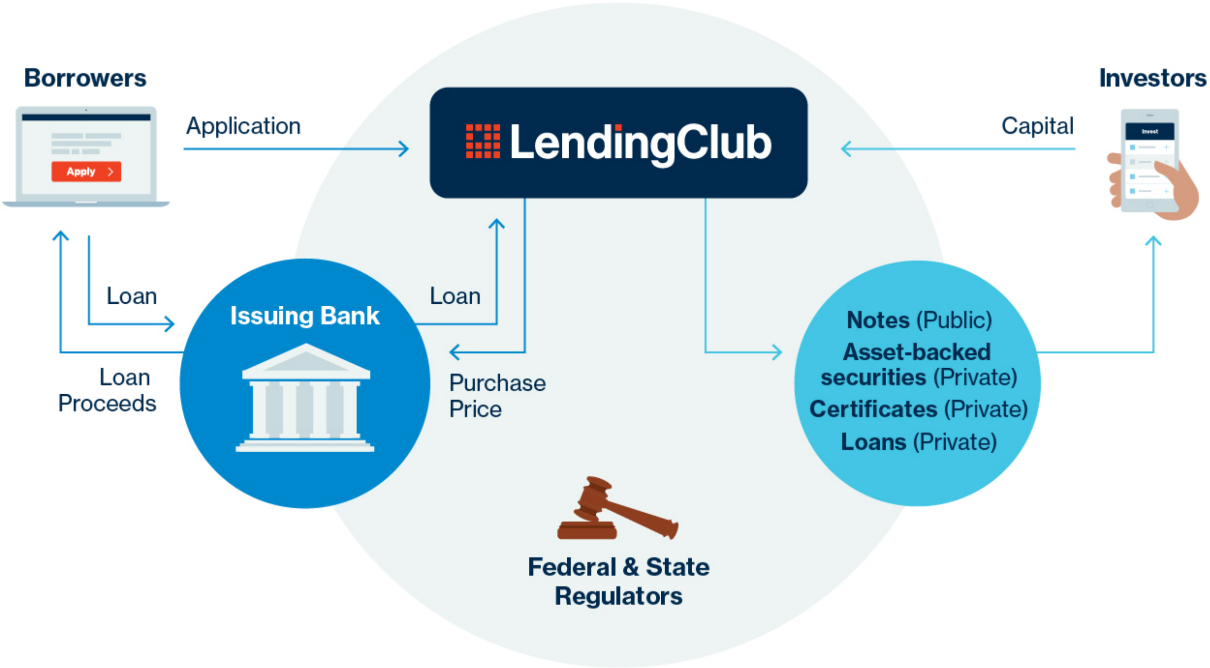
	scaled by the total loans in quarter t-1.	
$\Delta NPL_{i,t-1}$	The change in nonperforming loans from quarter t-2 to quarter t-1 scaled by the total loans in quarter t-1.	Call reports
$\Delta NPL_{i,t-2}$	The change in nonperforming loans from quarter t-3 to quarter t-2 scaled by the total loans in quarter t-1.	Call reports
$D\Delta NPL_{i,t}$	Dummy variable 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-1scaled by the total loans in quarter t-1.	Call reports
$\Delta CSLOAN_{i,t}$	The change of consumer loans from quarter t-1 to t scaled by the consumer loan balance in quarter t-1.	Call reports
$NPL\_CSL_{i,t-1}$	Non-performing 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 the 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
$\Delta UNEMP_{s,t}$	The 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
$\Delta POP_{s,t}$	The percentage change (in %) 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	LendingClub, Prosper and their

	their license for P2P lending business in a particular state.	10-K filings

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

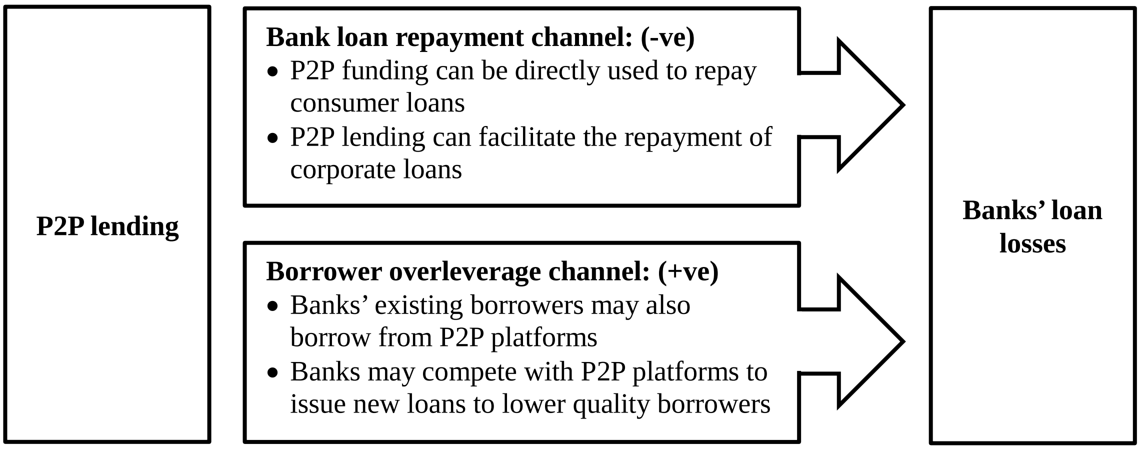
Appendix B: Figures and Tables

Figure 1 Loan issuance mechanism



This flow chart illustrates the loan issuance mechanism of P2P lending platforms during my 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 borrow money from P2P platforms, and banks may also compete with P2P platforms to issue new loans to lower quality borrowers. Either ways, banks' individual/household borrowers will become more leveraged. This borrower overleverage channel predicts a positive relation between P2P lending and banks' loan losses. While the bank loan repayment channel predicts the opposite and creates tension to this hypothesis, prior literature shows that borrowers can eventually be overleveraged even though the borrowed P2P funding is used to repay their bank debt. Therefore, on balance, I 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

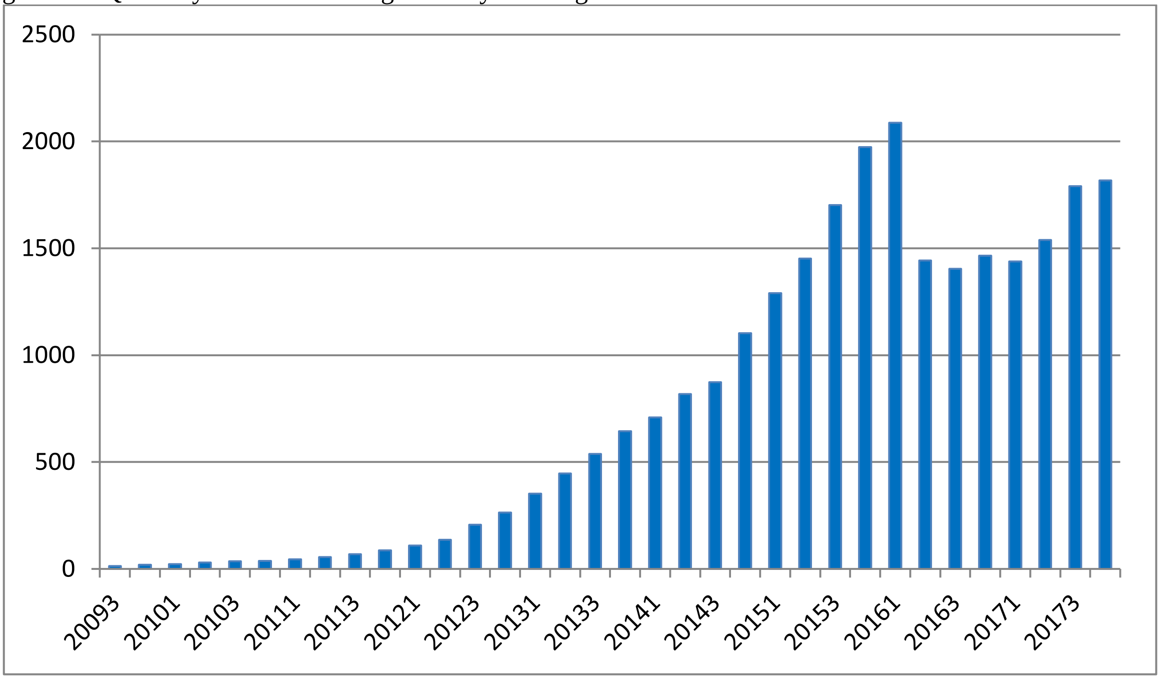
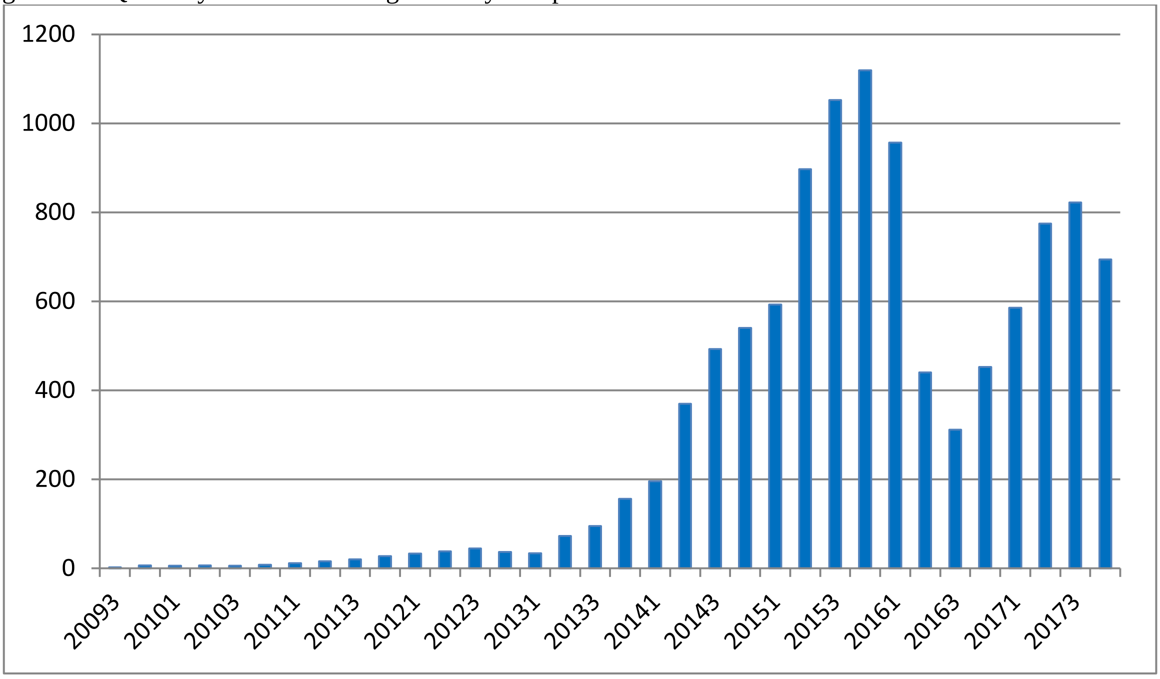


Figure 3B: Quarterly loan volume originated by Prosper



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

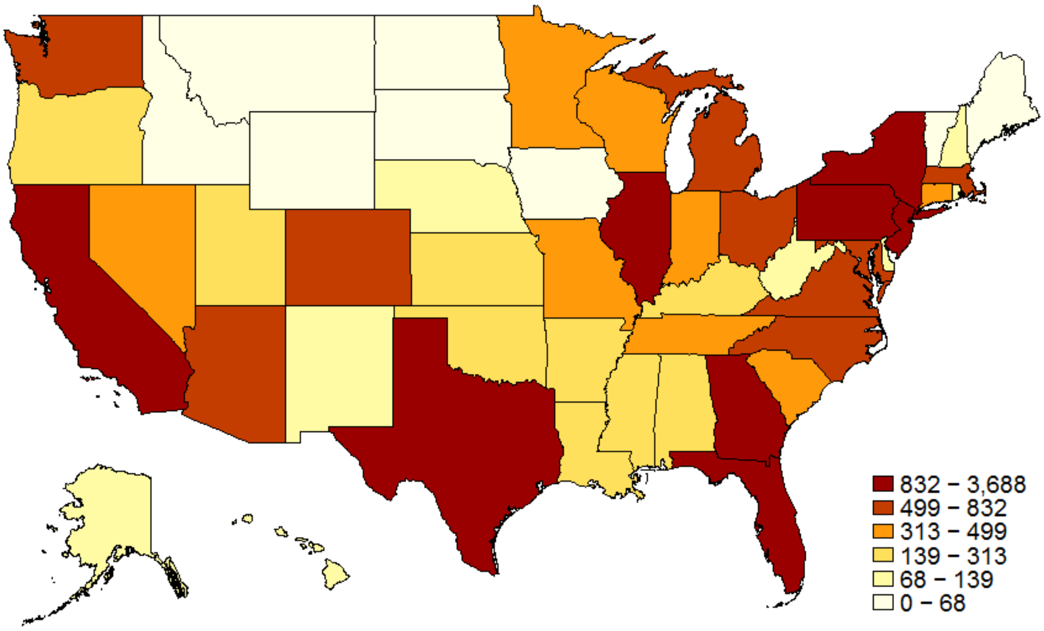
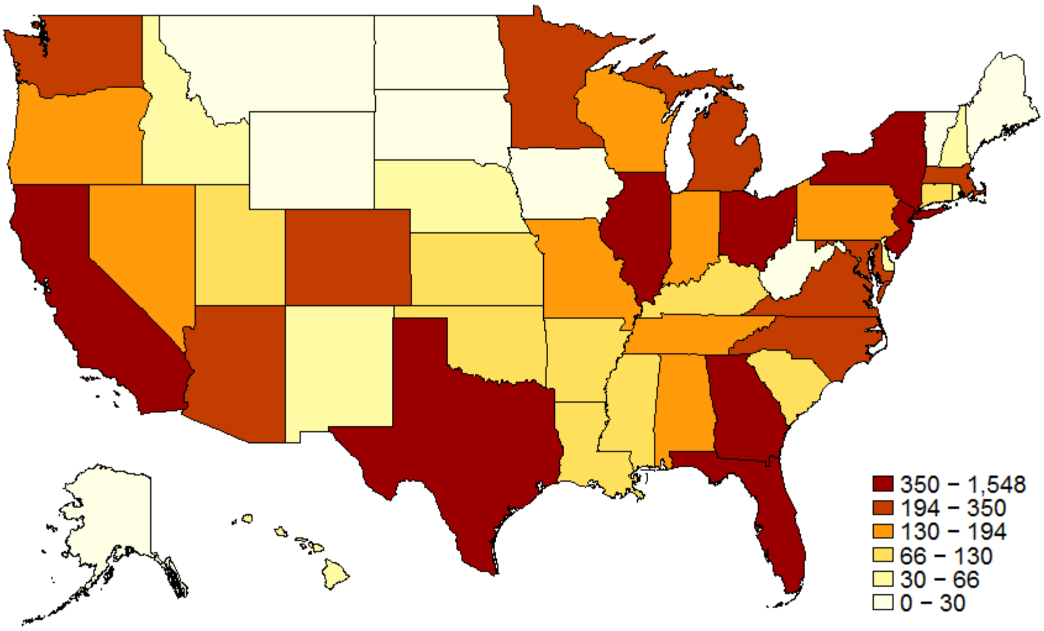


Figure 4B: Prosper's loan issuance by state



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

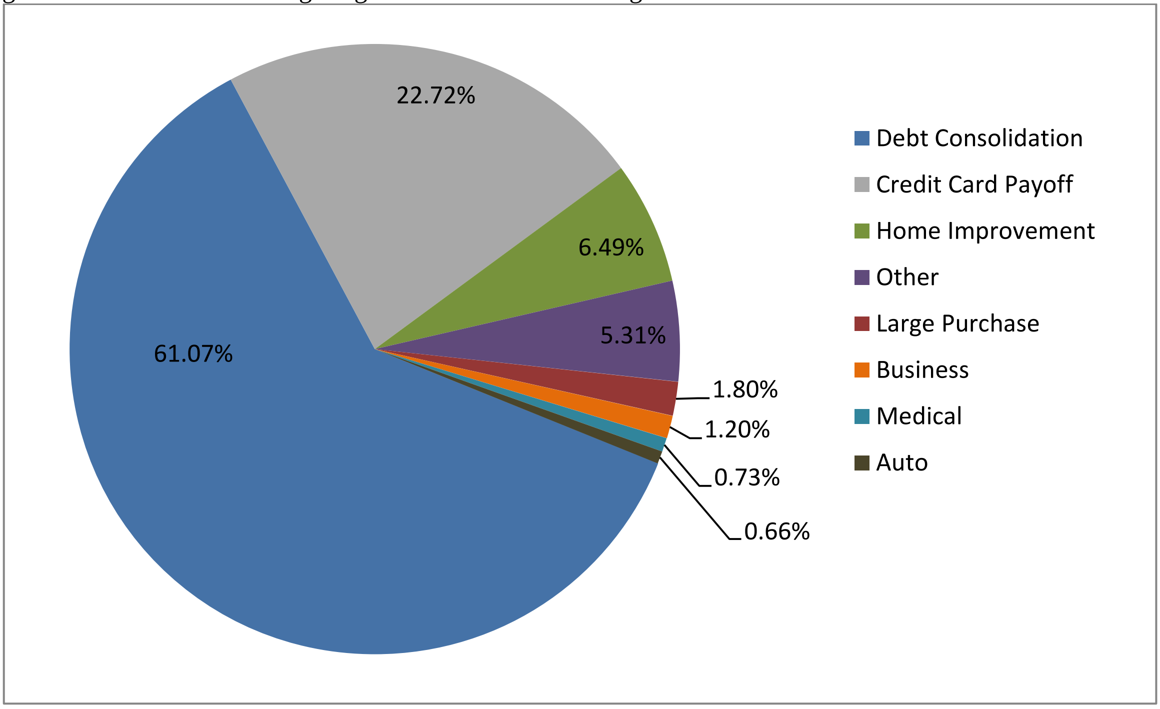
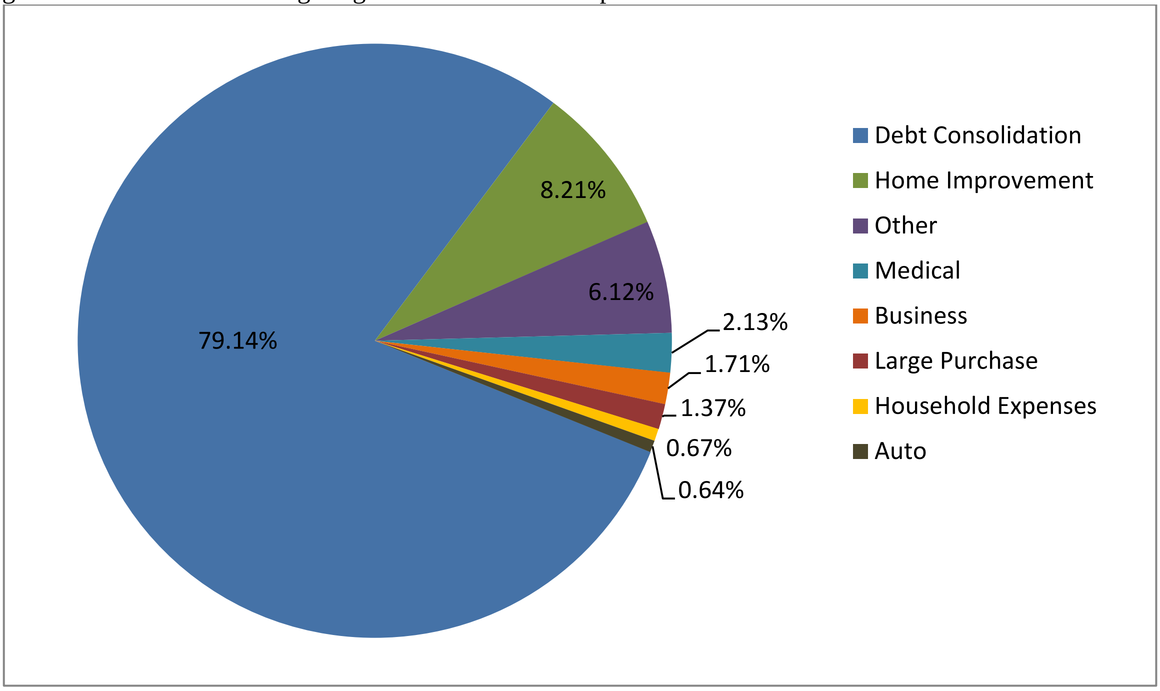


Figure 5B: Borrowers' funding usage distribution for Prosper



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 on LendingClub

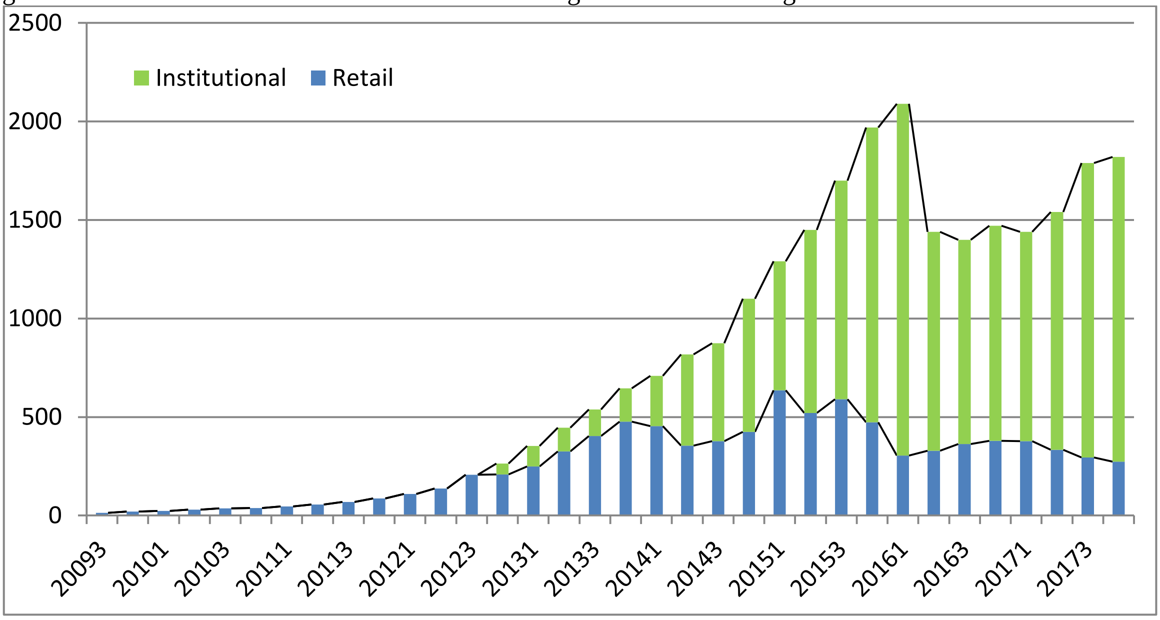
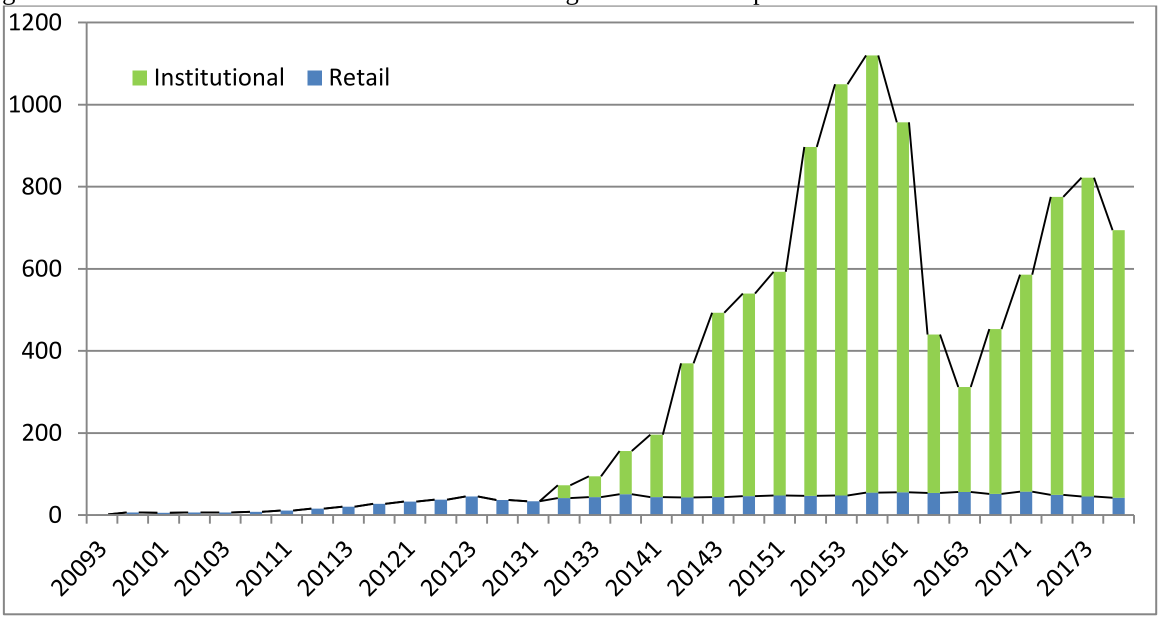


Figure 6B: Individual vs. institutional investors' lending volume on Prosper



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	S.D.	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 (S.D.), 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 The 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*****	**0.0040*****
	(5.84)	**(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	-0.0000
	(-0.44)	(-0.26)
$\Delta UNEMP_{s,t}$	0.0003***	0.0003***
	(3.03)	(2.79)
$\Delta HPI_{s,t}$	-0.0119***	-0.0072**
	(-3.44)	(-2.47)
$\Delta POP_{s,t}$	-0.0005***	-0.0005***
	(-3.07)	(-3.12)
$GDP_{s,t-1}$	0.0009	-0.0002
	(1.33)	(-0.26)
$UNEMP_{s,t-1}$	0.0001***	0.0001**
	(4.19)	(2.72)
$HPI_{s,t-1}$	-0.0019***	-0.0021***
	(-2.85)	(-3.04)
$POP_{s,t-1}$	-0.0015**	-0.0012*
	(-2.14)	(-1.90)
$AUTOD_{s,t-1}$	0.0027***	0.0025***
	(2.88)	(2.84)
$CCD_{s,t-1}$	0.0017**	0.0014**
	(2.18)	(2.04)
$MORTD_{s,t-1}$	0.0047***	0.0041***
	(4.91)	(4.29)
$DELINQ_{s,t-1}$	0.0001*	0.0000
	(1.83)	(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 aggregated 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, I use alternative model specification. In Column (1), I follow Kanagaretnam, Krishnan and Lobo (2010) to further control for beginning non-performing loans ($NPL_{i,t-1}$), current net charge-offs ($CO_{i,t}$) and change in non-performing loans ($\Delta NPL_{i,t}$). In Column (2), I follow Basu, Vitanza and Wang's (2020) specification to account for asymmetric loan loss provisioning. In Columns (3)-(5), I use alternative measures of P2P lending. In Columns (6)-(9), I use alternative sample to test the main hypothesis. In Columns (6) and (7), I exclude observations from Iowa and California, respectively. In Column (8), I 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 those banks' deposits. In Column (9), I exclude observations that may involve in M&A as their non-loan assets growth rate 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. I use as an IV the number of quarters since a both LendingClub and Prosper have obtained their license in a particular state. Column (1) presents the 1st stage results while Column (2) presents the 2nd 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 aggregated loan volumes (in billion US dollars) originated by LendingClub and Prosper during quarter t-1. To capture the extent of common lending, I use the level of consumer loan in quarter t-1 in Column (1) and the change of consumer loan from quarter t-1 to quarter t in Column (2). To ease the interpretation of the coefficient on the interaction term, I 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 aggregated loan volumes (in billion US dollars) originated by LendingClub and Prosper during quarter t-1. In Column (1), I use the overall delinquent rate as a proxy for the ex-ante likelihood of banks having overleveraged borrowers.

Specifically, the partition variable = the overall delinquent rate in state *s* for quarter *t-1*, i.e., = (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), I use the non-performing consumer loans in quarter *t-1*. To ease the interpretation of the coefficient on the interaction term, I 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) $LLP_{i,t}$
$\boldsymbol{LNP2P\_DC_{s,t-1}}$	**0.0089*** **	
	(3.24)	
$\boldsymbol{LNP2P\_OP_{s,t-1}}$	**-0.0176***	
	(-1.75)	
$\boldsymbol{LNP2P\_RT_{s,t-1}}$		**0.0155*** **
		(4.65)
$\boldsymbol{LNP2P\_IS_{s,t-1}}$		**0.0018** **
		(2.70)
$SIZE_{i,t-1}$	0.0013***	0.0013***
	(6.83)	(6.84)
$EBP_{i,t}$	-0.0200**	-0.0199**
	(-2.26)	(-2.25)
$CAPR1_{i,t-1}$	0.0013	0.0013
	(1.57)	(1.57)
$ALW_{i,t-1}$	-0.0055	-0.0057
	(-0.77)	(-0.80)
$HHI_{i,t-1}$	-0.0031***	-0.0031***
	(-3.68)	(-3.69)
$HETE_{i,t-1}$	0.0028***	0.0028***
	(7.95)	(7.99)
$\Delta LOAN_{i,t}$	-0.0025***	-0.0025***
	(-4.01)	(-4.03)
$\Delta GDP_{s,t}$	-0.0000	-0.0000
	(-0.18)	(-0.14)
$\Delta UNEMP_{s,t}$	0.0003***	0.0003***
	(2.87)	(3.13)
$\Delta HPI_{s,t}$	-0.0073**	-0.0084***
	(-2.55)	(-2.88)
$\Delta POP_{s,t}$	-0.0005***	-0.0006***
	(-3.22)	(-3.53)
$GDP_{s,t-1}$	-0.0003	-0.0004
	(-0.51)	(-0.55)
$UNEMP_{s,t-1}$	0.0001***	0.0001**
	(2.80)	(2.53)
$HPI_{s,t-1}$	-0.0019***	-0.0021***
	(-2.89)	(-3.11)
$POP_{s,t-1}$	-0.0012*	-0.0013*
	(-1.85)	(-1.98)
$AUTOD_{s,t-1}$	0.0025***	0.0029***
	(2.82)	(3.16)
$CCD_{s,t-1}$	0.0015**	0.0015**
	(2.16)	(2.16)
$MORTD_{s,t-1}$	0.0041***	0.0040***
	(4.31)	(4.25)
$DELINQ_{s,t-1}$	0.0000	0.0000
	(1.47)	(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), I divide the total P2P lending volume into two components according to loan purposes: loans for debt consolidation ($LNP2P\_DC_{s,t-1}$) vs. loans for other purposes ($LNP2P\_OP_{s,t-1}$). In Column (2), I 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 aggregated loan volumes (in billion US dollars) originated by LendingClub and Prosper during quarter t-1. In Column (1), I use earnings before provisions as a proxy for banks' capacity to accrue 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), I use regulatory capital ratio as a proxy for banks' capacity to accrue 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, I 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) $CO\_TTL_{i,t+1}$
$LNP2P_{s,t-1}$	**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 aggregated 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.